The Effect of Expertise in Norm Formation

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Abstract. The goal of the paper is to contribute to the ongoing discussion on the evolution of social norms. We bring together insights from different traditions of research with the hope that they may be complementary in explaining the connections between individual learning, action, and social rules or norms. Maurice Merleau-Ponty and Hubert L. Dreyfus are some of the thinkers who hold that the non-representational, holistic learning, absorbed coping, conformist learning and master-apprentice relationship is underestimated by both scientific and philosophical traditions. By combining this tradition with the existing literature on the evolution of social norms, our model aims to contribute to the field in that: (a) it adds novice and expert agents in a particular way into an evolutionary model of social norms such that population level outcome of individual learning is studied in a more explicit manner, and that: (b) conformism is tied to expert behavior, so that we interpret such a behavior with reference to being able to (partially) follow the evolution of the whole population compared to novice agents who are not able to receive any type of signals from population. We apply this framework to the PD game. Overall, our research is complementary to the works on the evolution of social norms.

Keywords: Norm formation, expertise, skillful coping, evolutinary games

1 Introduction

1.1 Philosophical foundations

How do we follow rules? Do we make calculations each and every time we follow a rule, as Herbert Simon would like us to think? Or, are there rules beyond our conceptual frameworks that we use practically, without (consciously) thinking about them, as Hubert Dreyfus insists? The answer to these and similar questions have become the subject of many studies in recent decades. The way one answer to these questions have much to do with the philosophical preferences and world-views.

This paper aims to contribute to our understanding of the relationship between individual learning of social rules and the evolution of social norms as a result of interaction between learning individuals. What makes some rules to stick, and some others to disappear?

Merleau-Ponty's embodied knowledge, Polanyi's skill and Dreyfus's work on relating these approaches to the modern cognitive science constitute the epistemological background of the paper. These thinkers underline the importance of unconscious coping with the world. They contend that the unconscious bodily skills or knowledge plays a primary role in one's understanding of the reality.

Thinking and learning processes related to some real life events do not seem to be precise and complete in their intentional and representational content: We do not make complex physical calculations when we are cycling, even if they might seem to be necessary to cope with a two-wheeler. To stop a car properly, we do not have to calculate the stopping distance, using numerous variables including the current speed, state of the brake pedal, friction between the road and tires, air resistance, and so on. We deal with the world with the help of some capacities that we cannot make explicit easily. These capacities seem to lack conscious representations or content. However, we still say I know how to ride a bicycle. Even if these capacities really rise from some kind of knowledge, this knowledge is quite different from knowledge that we use in the ordinary sense.

One of the most important contributions of Michael Polanyi to both continental and analytical traditions is his introduction of the concept tacit knowing. Tacit knowing, unlike explicit or codified knowledge, is very difficult or impossible to codify (to express in a language) and verbally transfer to people who do not know it. Knowledge of how to ride a bike, playing tennis or driving car are taken to be in this category.

It seems appropriate to describe how human beings acquire such skills or knowledge. And what makes an agent an expert one in real world? Basing his thesis on Maurice Merleau-Ponty's Phenomenology of Perception [15], Dreyfus defends that learning is not independent of the body of individuals. At least some knowledge becomes part of one's existence and it turns into a skill. They become endogenous to the decision-making process without representational content in the mind [7, 8, 13]. In essence, skills reduces the costly burden of rational calculation without compromising on the outcome. Yet coping skills are not equally bestowed upon the members of the population. That is why population consists of both expert and novice agents.

Polanyi [14], have a similar explanation: He argues that skills are performed on a subsidiary awareness level which would probably be considered to be unconscious by modern psychology. There is internalized personal knowledge, which becomes part of us accessed by this subsidiary awareness. It becomes part of us in the sense that a racket becomes a part of a professional tennis player or a stick becomes a part of a blind man. In both cases, unlike a newcomer (novice), an expert player does not need to pay attention to the use of the tool. The same is true for ordinary peoples use of their limbs, since they are skilfully managed to manipulate them.

What is more, human beings subsidiarily process assumptions of the theory when they do science. In our approach, a strategic competent beyond analyzing serves to simulate this subsidiary knowledge or skills. This strategic component will make the agent more component, while the agent gets more experience, just like human skills sharpen by time and experience. Both Merleau-Ponty and Polanyi claim that unconscious progresses play a pivotal role in our strategic actions and discredit attempts to analyze cognition ignoring these aspects of knowledge. They also seem to hold a holistic approach to learning and underline the importance of interaction between the world and human beings. So the general characteristics of skillful coping are as follows:

1. They are not accompanied by representational ideas and analytical processes. Instead they become part of the neural system or one's existence.
2. They are holistic in the sense that they are performed and updated considering numerous variables.
3. They improve by experience.

In our model, the holistic approach will be modeled by only expert agents having a sense of how the whole population acts and they will use a weighted (on being rational or conformist) update of their strategy using this holistic knowledge. To be less technical and more interpretive, Comparing with the novice learner who acts according to well-defined rules related to local variables, the expert learner also adapts the whole system.

1.2 Evolutionary foundations

There is also an extensive literature about the complexity of decisions and ways of bypassing these complexity: Bounded rationality in Simon's sense highlights our limited capacity to engage in complex issues. Hence, we economize on our limited cognitive capacities by adhering to evolved rules of thumb. Evolved social norms and institutions are part of this story. They are embedded in our ways of thinking and acting [18].

Social dimension of learning is important, since society reduces the cost of acquiring skills by individuals in certain social environments [3]. Acceptance of several social norms by individuals is an example. On this ground, evolutionary approach emphasizes that individual learning takes place in an environment shaped by interactions within the society.

When individuals make decisions, they usually do not take the effects of their actions on society into account [10]. However, these feedback effects are of utmost importance in evolutionary thinking. As Gintis [9] points out, beliefs, constraints and preferences of others matter. Individual learning makes sense in a framework where reconciliation of individual and social outcomes are addressed properly. Social interactions should be able to reconcile individual behavior and social outcomes [2].

It seems that conformity requires certain skills like sensing the general tendencies of the society, applying these to new situations and so on. If conformity requires certain skills to be acquired, then it would be appropriate to assume that experienced agents are more likely to act accordingly. So in a crude classification, there are novice and expert agents in the society concerning the decisions about the social norms and these agents change their tendencies according to feedback they get. What type of social outcomes are expected under such a dynamic, diverse and strategic interactions? The answers are important, simply because of the observation that similar norms (e.g. traffic rules) are accepted by one group of people while rejected by some others. In the paper, we try to understand how a social trait is accepted or rejected by society when society consists of novice and expert learners in the above sense. In essence, how a social trait is formed and/or replaced by a group of heterogeneous learners acting strategically? In technical terms, the question could be formulated as Why certain social traits are ESS (Evolutionarily Stable States), while some others are not in a population of heterogeneous learners?

Below we propose a simple model in which we bridge together two seemingly different ways of looking at learning. The evolutionary theory in the spirit of Maynard Smith in biology and Robert Sugden [16] in economics tend to assume that learning of agents do not produce skillful coping in the process and the evolution of social norm is a result of the evolutionary process. We add to this line of thinking the point that as individuals become experts the interaction between novice and expert players create novel outcomes that may shed light on the process of norm formation. In other words, under certain conditions rule following may become a tool for experts to cope with the environment. This situation, in turn, creates a virtuous circle that reduces transactions costs of following a rule at the social level.

2 The Model

2.1 General setting and assumptions

We use the Prisoners Dilemma (PD) game to study the formation of social norms and rule following behaviour. Consider the evolutionary process in two parts as follows: (a) A group of novice individuals play a Prisoners Dilemma (PD) game; (b) On the other hand, expert players consider general tendencies in the population besides considering payoff matrix of the PD game.To be able to convey the ideas behind this separation, consider the evolution of traffic rules. The traffic rules are obstacles for an individual assuming that there is only one individual since the driver following the rules will lose time. However, the very same rules regulate the traffic in society. Assume that, there are two groups of individuals. The first group of individuals, novice players, behave according to calculated payoffs with mistakes determined by a selection parameter. Their update rule depends just on the payoff calculation and selection parameter (allowing them to make mistakes). In this case, agents tend to imitate successful individuals. Since the game played is a PD game, evolution leads this population to the defection.

We are interested in the question how does the existence of expert players affect the equilibrium? Here, the second group of individuals, namely expert players, use conformist update rules along with the standard payoff calculation and follow the tendencies of the population. Experts agents represent people who internalize the norms of society. Conformist learning serves as a tool to keep population close to the established norm or norm to be established (see the graph below). This rule is effective only in populations forming norms. Thus, we assume that the conformist learning parameter is proportional to the frequency of cooperators in the population. Below, we present our model.

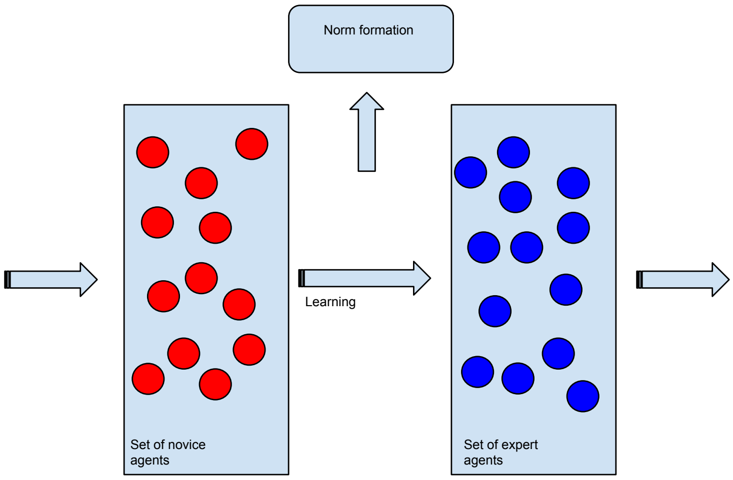


Fig. 1. Graphical representation of the model

As seen from Figure 1, we assume that novice players become expert by time. The dynamics of expert and novice agents are determined as follows such that whenever a novice player becomes skilled enough, this novice player becomes an expert. At the meantime, a new novice player is added to the population and an expert agent vanishes. Hence, the population size remains constant along with the frequencies of novice and expert agents i.e. population is in equilibrium in terms of expert and novice players. This assumption helps us to answer our question regarding the effect of expert players in the population for norm formation. Making the frequency of novice and expert players time-dependent can be considered as a research question for future studies.

Formally, we assume that when there is only one driver, s/he can reach her/his destination in α minutes without following any traffic rule. The very same driver completes the same task in $a > \alpha$ minutes if s/he follows the rules.

Using the above assumptions, now we could consider the case where the driver is not alone. We have the following cases: (a) If the driver is not alone, and in a group of individuals following traffic rules then s/he reaches his destination in a minutes; (b) if the society follows the rules but our agent does not then s/he reaches her/his destination in $c \in (\alpha, a)$ minutes; (c) unless the society including our agent follows the rules the situation gets worse and time of the journey becomes $d > a$; (d) unless the society follows the rules but our agent does, then s/he gets a greater harm and reaches her/his destination in $b > d$ minutes. Hence, we can construct our normal form symmetric two-strategy game with strategies C (rule follower) and D (non-rule follower) as follows:

$$M = \begin{pmatrix} -a & -b \\ -c & -d \end{pmatrix}$$

where $c < a < d < b$ and thus the game is a Prisoners Dilemma. In evolutionary setting the ESS is (D,D) which is Pareto dominated by the Pareto optimal outcome (C,C).

This fact suggests that each individual in the population as a rational player is driven to be a non-rule follower. However, this is not always the case. To be able to examine the formation of norms, we first consider a population of novice and expert individuals of size N. Novice agents are the ones who calculate their payoff and play imperfectly according to these payoffs and experts are the ones who calculates the payoffs relatively better. Suppose that the frequency of novice and expert cooperators (rule followers) are given by x_n and x_e.Thus one can calculate the payoffs of novice cooperators and defectors as follows:

$$\Pi^C = (b - a)x - b \text{ and } \Pi^D = (d - c)x - d,$$

where $x = x_n + x_e$. Now we introduce the microscopic update rules for novice players following [17]. Suppose that two individuals from the population are drawn randomly one of which is called the focal agent. Focal individual imitates the other agent (role model) with some probability according to payoff differences. This probability is calculated as follows:

$$q_n = \frac{1}{2} + \frac{w_n}{2\Delta p}(\Pi^r - \Pi^f) \tag{1}$$

where Π^f and Π^r represents the payoffs of focal agent and the role model and Δp is the maximum payoff difference guaranteeing that the probability stays in between 0 and 1. Here the parameter w_n is the selection parameter determining the noise intensity for novice players. Note that novice players are used by Kandori et. al [11] and they assume that these players choose one of the two strategies randomly. In our setting, we assume that the selection parameter w_n is small so that the game dynamics affects the choice of the players. However this assumption also implies that novice players choose their strategies almost randomly.

The probability given in equation (1) describes the imitation dynamics of novice players. These players are to become expert agents by time. Thus whenever a novice individual is chosen there are two update possibilities. One is strategy update by imitation and the other is the probability of becoming an expert agent. Above we defined the former one. Now consider the latter update rule. Suppose that a novice agent is chosen as a focal agent. S/he updates her/his strategy using the imitation probability defined by q_n.

Now we introduce the update rules of the game for expert players. Hence, existing expert agents (whose frequency does not change by time) use conformist update rules with a weight proportional to the frequency of rule followers. In other words, the population consisting of rule following individuals forces expert individuals to keep pace with the population rather than only acting to maximize their individual payoffs.

To be able to model conformism based update rule, we consider the payoff based learning rule with the following coordination game payoff matrix:

$$C = \begin{pmatrix} s & 0 \\ 0 & s \end{pmatrix}$$

Clearly the payoff to each strategy is proportional to its frequency in the population. Thus the strategy with highest frequency in the population is favoured by the payoff matrix. We define our new and frequency dependent payoff matrix as follows:

$$\tilde{M} = xC + (1 - x)M \tag{2}$$

where x is the frequency of rule followers. A similar payoff matrix has been considered in [12]. Now construct the update rule for expert agents. An expert focal agent uses above defined payoff matrix $\tilde{M}$ to update his/her strategy. Note that the agent does rational calculations and plays the PD game with a weight of non-rule followers i.e. s/he employs rational calculations proportional to the frequency of rational players. On the other hand, the very same agent has a tendency to follow the rules proportional to the frequency of rule followers. We consider expert agents using a similar update rule given as follows:

$$q_e = \frac{1}{2} + \frac{w_e}{2\Delta\tilde{p}}(\tilde{\Pi}^r - \tilde{\Pi}^f)$$

where $w_e, \Delta\tilde{p}$ and $\tilde{\Pi}$ are the selection parameter, maximum payoff difference and payoffs calculated according to the matrix $\tilde{M}$. Expert players update their strategies with less mistakes. Thus we suppose that $w_n < w_e$.

2.2 Markov chain and its mean dynamics

Here we set up the update rules for two types of individuals. Suppose a novice player is chosen from the population as the focal individual and another player is chosen as the role model whose payoffs are given as Π^f and Π^r. Then the novice agent playing C updates her/his strategy to D with probability

$$q_n^1 = \frac{1}{2} + \frac{w_n}{2\Delta p}(\Pi^D - \Pi^C).$$

On the other hand, the update probability for an expert cooperator is given by

$$q_e^1 = \frac{1}{2} + \frac{w_e}{2\Delta\tilde{p}}(\tilde{\Pi}^D - \tilde{\Pi}^C)$$

where $w_n < w_e$. Note that these players use the frequency dependent payoff matrix given by (2). Update probabilities of expert and novice cooperators can easily be obtained from the definitions and are equal to 1-q_n^1 and $1 - q_n^1$.

Suppose that the frequency of expert players is denoted by e. Recall also that the frequency of expert and novice agents playing the strategy C are denoted by x_e and x_c, respectively. Clearly the frequency of the agents playing the strategy C is given by $x = x_n + x_e$. We define the transition probability of an increase in the frequency of experts playing strategy C as follows:

$$P\big(x_e(t+1) = x_e(t) + \frac{1}{N}|x_e(t)\big)= x(e - x_e)(1 - q_e^1)$$

where $e - x_e$ is the probability of choosing an expert agent playing D, x is the probability of choosing an agent playing C as role model. Similarly other transition probabilities are given as following:

$$\begin{aligned}
P\big(x_e(t+1) = x_e(t) - \frac{1}{N}|x_e(t)\big) &= x_e(1 - x)q_e^1,\\
P\big(x_n(t+1) = x_n(t) + \frac{1}{N}|x_n(t)\big) &= x(1 - e - x_n)(1 - q_n^1),\\
P\big(x_n(t+1) = x_n(t) - \frac{1}{N}|x_n(t)\big) &= x_n(1 - x)q_n^1.
\end{aligned}$$

We can easily get the mean vector fields as follows:

$$E\big(x_e(t+1) - x_e(t)|x_e(t)\big)= \frac{1}{2N}\big(ex - x_e + \frac{w_e}{\Delta\tilde{p}}(x_e + ex - 2xx_e)\big)(\tilde{\Pi}^C - \tilde{\Pi}^D),$$

and

$$E\big(x_n(t+1) - x_n(t)|x_n(t)\big)= \frac{1}{2N}\big((1-e)x - x_n + \frac{w_n}{\Delta p}(x_n + (1-e)x - 2xx_n)\big)(\Pi^C - \Pi^D).$$

Thus, the differential equations modeling the game dynamics can be given as follows:

$$\begin{aligned}
x_e' &= ex - x_e + \frac{w_e}{\Delta\tilde{p}}(x_e + ex - 2xx_e)(\tilde{\Pi}^C - \tilde{\Pi}^D),\\
x_n' &= (1 - e)x - x_n + \frac{w_n}{\Delta p}(x_n + (1 - e)x - 2xx_n)(\Pi^C - \Pi^D).
\end{aligned}$$

Relation to original replicator equations can be observed easily by taking the limit as $e \to 0$. In this case $x_e \to 0$. and thus $x_n \to x$. Therefore we get from the second equation

$$x' = \frac{w_n}{\Delta p}(x - x^2)((a + d - c - b)x + b - d)$$

which is the original replicator equation for two strategy symmetric games. As $e \to 1$ we get a quartic right hand side due to the frequency dependent payoff matrix (2). It is easy to show the deviation between Markov chain and differential equation model is probabilistically bounded as done by Benaim and Weibull [1].

2.3 Determining the basin of attraction via simulations

Here one can easily show that the equilibrium points $(0,0)$ and $(e, 1-e)$ are both locally stable. We use simulations to be able to study the effect of expertise on basin of attraction for each stable fixed point of the above given system of equation. First note that the quantity that we are interested in is the frequency of rule followers $x = x_n + x_e$. For the sake of simplicity we will consider the following PD and conformist update matrices

$$M = \begin{pmatrix} -0.2 & -1 \\ 0 & -0.6 \end{pmatrix} \text{ and } C = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

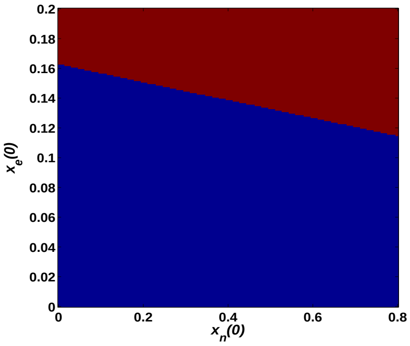
Fix $w_e/\Delta\tilde{p} = 1$ and $w = w_n/\Delta p$ denote . Thus our parameter region becomes $\{w, e\}$.

Effect of the selection parameter w and frequency of expert players e have been illistrated in Figure 2. It is easy to see that by comparing panels (a) and (b), (c) and (d), and (e) and (f) as learning/selection parameter w of novice players decreases, basin of attraction area of rule followers (cooperators) is increases. In the case of slow learning novices (panels (a), (c) and (e)), our simulations also shows that the basin of attraction of cooperators depends mainly on frequency of expert rule followers. For example, it is clearly illustrated that cooperators can take over the whole population even if the initial frequency of expert rule followers is 0.16 and that of novice rule followers is 0 in panel (a). So it can be concluded that the norm foms if there are sufficient amount of expert rule followers.

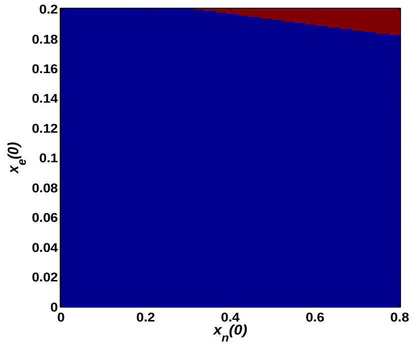
In the model, distinct from standard evolutionary models, individuals follow a tacit learning process and become experts in following the rule as time passes. Yet, they also look at other individuals and make the decisions based on their learning and other peoples behavior, which means that a threshold value of obeying the norm evolves during the process, as individuals adjust their behavior watching other people. Therefore, a social norm is established when a certain number of people internalize the rule. For experts a social norm becomes part of skillful coping of the individual. Thereby, in addition to the initial conditions regarding novice and expert cooperators/defectors, learning parameter has an effect on the basin of attraction of rule following/not following outcomes.

3 Discussion: From individual learning to social norms

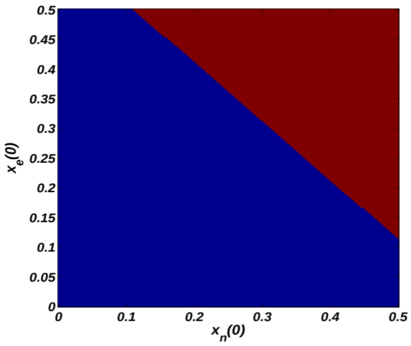
Hubert L. Dreyfus and Stuart E. Dreyfus claim that modern philosophy of mind and artificial intelligence research programs underestimate the importance of non-representational learning, namely learning that is not intermediated by representations in the mind or the brain. Hubert L. Dreyfus, describes five discrete stages of learning from novice to expertise: Novice, advanced beginner, competence, proficient, expertise. Throughout this process, individuals acquire new knowledge and behavior patterns. While in the first few stages the learner acts in rule-driven manner, at later stages of the process, experience is assimilated by



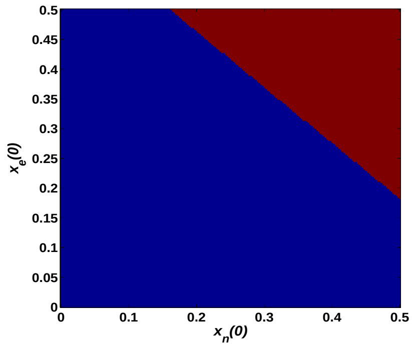
(a) Basin of atraction for each strategy with parameters $w = 0.1$ and $e = 0.2$



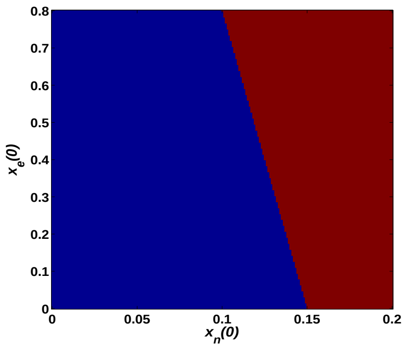
(b) Basin of atraction for each strategy with parameters $w = 0.5$ and $e = 0.2$



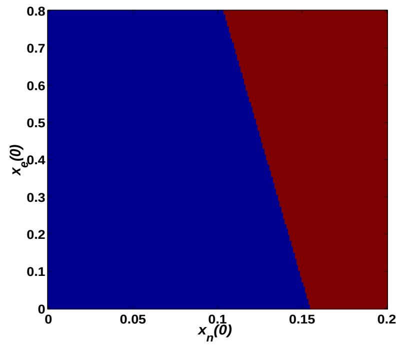
(c) Basin of atraction for each strategy with parameters $w = 0.1$ and $e = 0.5$



(d) Basin of atraction for each strategy with parameters $w = 0.5$ and $e = 0.5$



(e) Basin of atraction for each strategy with parameters $w = 0.1$ and $e = 0.8$



(f) Basin of atraction for each strategy with parameters $w = 0.5$ and $e = 0.8$

Fig. 2. Red region represents the basin of attraction for cooperation in each panel.

him/her, in such a way that intuitive reactions of a theoretical type replace reasoned responses. The process of climbing the ladder of learning could be summarized as recognize more and analyze less. While the learner becomes expert, s/he recognizes more patterns, and acts accordingly by absorbing new coping mechanism. And throughout the same process, she becomes less procedure-driven, less analytical and more intuitive([6, p. 16-35] and [5, 8]).

This idea is implemented in a sketchy way to base for future studies. And the results suggests that the proportion of expert agents matters when it comes to the question whether or not a cooperative trait to become ESS. There are several possible improvements of the model. For example one can study the cases in which the frequency of expert agents evolves by time towards the equlibrium point e or the stochastic model is placed upon a network strructure.

Our approach treats the evolution of social norms as a non-cooperative common interest game, since there are no enforceable restrictions on the acceptance and/or rejection of a certain norm at the social level [2]. It is common interest since a threshold level of individuals is necessary for each and every norm to be accepted by society. In that condition it has higher returns for individuals as well as society [2]. Notwithstanding that, since norms are self-reinforcing, people want to conform them when they expect everyone else to conform [18]. Therefore, although a norm may provide a basis for beneficial interactions, violating it may be beneficial for opportunistic individuals. The proliferation of socially beneficial norms, e.g. cooperation instead of defection is then explained by group selection theory in which adoption of certain norms are beneficial for the group who adopt it [3, 4].

Yet, agents, i.e. learning individuals, in our model do not only imitate the others under the pressure of evolutionary selection. There are several ways to learn and transmit norms. We focus on conforming to the environment, and learning from our past experience. This is why learning parameters assume different values for novice and expert players in the model. Bowles [2] and Young [18] list some other factors such as expected higher gains, fear of punishment, signaling, following the lead to explain why individuals conform a social norm.

In our model, novice agents acts by analyzing the noisy information about the payoff of other agents. When they become expert on the other hand, their choices determined by the general tendency in the population, which sometimes contradict with individual interest. Just like the expertise described by Dreyfus, their tendencies are more stable, as if they embodies the knowledge about the game.

Our results suggest that proportion of expert cooperators in a society makes acceptance of a norm easier. Even if expert agents make decisions contradicting with their short-term-self-interests, in the long run, the members of the populations which accepts the cooperative norm with the cost of reducing their individual profit will have a better expected payoff. An interpretation following from our results is that expertise and embodied knowledge seems favoring cooperation.

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