

Social Learning vs. Individual Learning: A Genetic Algorithm Approach

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Abstract

The paper attempts to model the trade-off between social and individual learning strategies within a simple overlapping generation model. We employ a genetic algorithm and a simple payoff function to observe the optimum mix of strategies adopted by heterogeneous agents under this framework. Our stylized findings are that there is a preference towards social learning strategies when the pay-off of the agents are in close proximity to the optima. We also find evidence of a trade-off between social and individual learning strategies caused by increasing the search cost associated with individual learning strategies.

1. Introduction

The manner of formation of strategies has been a topic of great interest especially among anthropologists and sociologists. Numerous theories have been proposed regarding the manner in which an individual acquires their preferences over their lifetime. In this regard, two mechanisms of learning are apparent throughout the literature: Social and individual learning. Social learning refers to knowledge acquired through interaction with other con-

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specifics (related or otherwise). Meanwhile, individual learning encompasses knowledge acquired through an individual's interaction with the environment. The former mechanism of learning is drawn from a large pool of literature on cultural learning and evolution by Boyd and Richerson (2005). The choice of which strategy to play is a function of the pool of strategies played in the previous period. This is essentially saying that the richer the history of strategy spaces the less likely an individual is to explore new strategies. Naturally, this implies that there is a possible trade-off between choosing to explore new strategies (via individual learning) instead of exploiting a large set of existing strategies. Another reason for such trade-offs to arise would be the cost of exploring new strategies. Innovation of new strategies comes at a biological cost to the individual given that the new found strategy is far from optimal. However, it does pose benefit for the species as a whole since it expands the strategy space (or the history of strategies) for future generations.

Our objective is to simulate a simple environment with two types of agents (young and old) where each agent is maximizing a biological fitness function. The agents choose in each period what fraction of strategies are formed via social learning. The agents are allowed to pick a convex set of strategies between social and individual learning. Simply put, the agent's final strategy set may include a share of previous strategy sets and a share of new strategies. We are interested in the optimal strategy mix generated using genetic algorithms. Genetic Algorithms have proven to be a representative mode of learning by agents under the assumption of limited rationality. Interestingly it was designed as a search process rather than an optimization process by

Holland (2012). The algorithm adopted is based off of evolutionary theory and models a learning by doing process for the agents. This is more representative of the learning process observed among agents under experimental environments. It is also less restrictive in the assumptions made about the agent's ability to have perfect foresight. The model does not require the agents to have any information about the various complexities of the environment. Furthermore, heterogeneity among agents can be captured using this approach. Finally, it offers computational advantages in cases of problems with expectations under uncertainty where a closed form solution of the problem is not feasible.

2. Relevant Literature

In the following section we draw from literature ranging across multiple disciplines to establish a theoretical foundation of our model. The foundational blocks of the model including definitions of key concepts are adopted from relevant literature. The literature reviewed is categorized in terms of the key concepts and definitions. In the following sub-sections we elaborate on certain key concepts and definitions; mainly, we devote special attention to the concepts of social learning and individual learning from a multidisciplinary perspective. We then discuss the theoretical underpinnings for the trade-off arising from making choices between these two alternative strategies of information gathering.

2.1. Social Learning

The discussion of social learning as a mode of acquiring strategies is influenced by the cultural intelligence hypothesis put forward by van Schaik and Burkart (2011)¹. The literature in the disciplines of anthropology, biology and sociology mostly concern themselves with the broader definition of culture. However, there is a large discrepancy surrounding the definition of the term culture. A brief review of the literature on this issue is sufficient to show the wide range of discrepancy regarding what culture means. Kroeber and Kluckhohn (1952) finds over 150 definitions of culture². Given the linguistic constraints surrounding the use of the term, the paper abstracts from discussions on cultural learning. Instead, the paper focuses on an aspect of cultural learning that is cited in numerous definitions across multiple disciplines according to Kroeber and Kluckhohn (1952), i.e. Social Learning. Social learning has been defined as a mode of imitative learning whereby an individual learns through observing other conspecifics. Galef Jr and Whiskin (2008) find evidence of such learning mechanism among animals, specifically rats. They study the learning behavior of rats under an uncertain environment. Their findings show that rats prefer to learn from their conspecifics when identifying between protein (which they cannot easily identify) and sodium (which they can easily identify). The fact that rats show such strong influences of social learning begs the question of whether this is an evolutionary response. Rogers (1988) argues that social learning can improve the

¹See also Boyd and Richerson (2005), Henrich and McElreath (2007) and Tomasello et al. (1993) for discussions on cultural learning

²See also Birukou et al. (2013) for discussions on the evolving definition of culture.

expected biological fitness of the individual within the species. By learning from observation or imitation of their conspecifics, a rat for example, can learn to identify which food is poisonous. Boyd and Richerson (2005) make similar remarks. So if social learning can improve the biological fitness of the species then there are grounds to argue that this strategy is driven by natural selection. Since according to Fisher's Fundamental Theorem of Natural Selection, selection strives to increase mean biological fitness of the species. Other animals have also exhibited such social influences in their learning mechanism. In fact, the first notable evidence of cultural learning among animals surfaced as the identification of birdsong dialects by Marler and Tamura (1962) was combined with laboratory findings of social learning of these songs among birds. Furthermore, Fiore et al. (2020) find evidence of food washing behavior among Japanese macaques. For the purposes of our investigation we refer to the definition of social learning adhered to by Boyd and Richerson (2005) and Rogers (1988). As the literature shows, evidence of social learning is quite pervasive in the animal world. But what implications do they hold from a social and anthropological perspective.

Is a herd mentality an evolutionary response? Is imitating a fixed set of past strategies augmenting the biological fitness of our species as a whole? From the perspective of social sciences the influences of social learning in our learning mechanism can have interesting behavioral implications. It definitely sheds interesting insight into matters of preference formation among consumers. Duffy et al. (2019) design an interesting sequential choice experiment where a number of agents are required to sequentially guess the binary state of the world prior to realisation of the state. They are given the choice

of social information (guesses of everyone who guessed prior to the agent) and a noisy private signal. Their findings show that initially the agents have a bias towards choosing the private signal, albeit noisy. However, for agents lower down the line (who guess later), there is an apparent bias towards the social information. This is an insightful analogy as it depicts the evolutionary benefits of social learning as a form of collective intelligence. What is also very interesting (and intuitive) in their findings is that the social information is only optimal for agents lower down the guessing order. These agents clearly have a bias towards social information as they have access to a longer history of information to choose from. Hence, the agents are faced with a choice of either acquiring noisy information or resorting to a long history of past information. Other experimental approaches to modelling social learning have been conducted in the Economics discipline, for example, Schotter and Sopher (2003) conduct a multi period prisoner's dilemma game with multiple subjects to test the reliance of the subjects towards collaboration through social exchange of information. Next we look at the alternative to the social learning mechanism, Individual Learning³.

2.2. Individual Learning

Individual Learning is defined as the acquiring of information through physical interaction with the environment. A useful way of thinking of this form of learning is through the analogy presented in the experiments of Duffy et al. (2019). In that experiment individual learning was analogous to choos-

³This does not imply that there are only two mechanisms of learning. However, for the purpose of this paper we restrict the space of our analysis to these two alternative choices

ing the noisy private signal. The noisiness of the signal suggests that there is some uncertainty surrounding that signal. Mcelreath et al. (2008) further elaborate on this uncertainty surrounding individual learning strategies. They highlight that interacting with the environment can entertain the possibility of incurring biological costs. However, such a personal cost can serve as a benefit for future generations. It is useful to employ a thought experiment to best illustrate the dynamics of an individual learning strategy. Suppose a hypothetical species of rats is initialised in a foreign environment with multiple food sources. The rats are now required to navigate these food sources to find the ones which are optimal for their biological fitness. Initially, without any history to rely on, the rats must improvise and interact with their environment. Certain rats will pick the poisonous food incurring a personal cost. However, if these rats survive they can transmit their information to future generations of rats. Hence, by adopting individual learning strategies in the initial phases the rats may incur a personal cost. However, this personal cost can act as a group benefit as it expands the historical strategy space for future rats. Alternatively, you can think of it as reducing the strategy space by getting rid of non-optimal food choices⁴. Barrett et al. (2019) argues that individual learning is a type of phenotypic plasticity. It is a favorable strategy over copying past strategies when there are no past strategies to rely on, or if the past strategies are no longer relevant. This can happen when the environment changes, thus making the information drawn from interacting with the previous environment unreliable. There are other

⁴See citeneadle2020testing for an interesting study on how chimpanzees acquire nut-cracking behavior via individual and social learning.

reasons that can make information attained via social learning unreliable. Evdokimov and Garfagnini (2020) asserts that social cues of information can often be unreliable due to the transmission mechanism between generations. In an experimental set-up similar to that conducted by Duffy et al. (2019), they see a bias among subjects for individual private information over the social information. They argue that this bias is generated by the inability of the subjects to transmit the social information accurately. All of these issues raise the following question: Is there a trade-off between these two alternative modes of learning? Furthermore, which strategy is encouraged by natural selection? That is, which of these strategies generate higher biological fitness?

2.3. Trade off between Social and Individual Learning

The existence of a trade-off between these two alternate mechanisms of learning should be quite apparent from the contrasting definitions of the two strategies. However, the nature of the trade-off nor the source of it is clear from the literature. Grove (2019) alludes to changing environment as the source of the trade-off between the two types of strategy. Using a simulation of overlapping generations, he shows that individual learning strategies are in higher frequency among the population when the environment is changing rapidly. This theory is further corroborated by Barrett et al. (2019). On the other hand, experiments conducted by Duffy et al. (2019) have shown that accounting for the search cost of individual learning strategies can show a preference towards social learning by the agents. There are other factors involved in the generation of a trade-off. For instance, the method of transmission of strategies via social learning is an important factor here. If there

is noise in this transmission process then that can give rise to another reason for a trade-off. This is shown by Evdokimov and Garfagnini (2020) and Belavadi and Hogg (2019).

However, to our knowledge very few studies have compared the effects of social learning and individual learning on biological fitness in a model that incorporates all of these possible changes. Mcelreath et al. (2008) conduct an analysis of the fitness of the two different types of strategies (including other variant strategies) individually. This does not allow us to make reasonable comparative statements about the two strategies. The closest study we could find that covers all parameters underlying the trade-off is by Grove (2019)⁵.

3. The Theoretical Model

We use an overlapping generations model that is computationally similar to that of Arifovic et al. (1997) but theoretically more representative of the specifications followed by Grove (2019). Our world is defined by a continuum of agents, $i \in (0, 1)$ at any point in time, t . These agents are defined by their phenotype, P_{it} . Following the specifications of Grove (2019), we formally define it as:

$$P_{it} = \alpha_{it}X_i(t-1) + (1 - \alpha_{it})X_{it} \quad (1)$$

$X_i(t-1)$ refers to the strategies that are copied from the previous period, while X_{it} represents strategies that are randomly generated without any inference

⁵The model presented in Grove (2019) allow us to observe the proportion of individual learning strategies played under various specifications of the information cost and environmental change.

from history. Naturally α is the variable of interest here. The evolution of α throughout the population will show the share of the population preferring social learning. In every time period, t , an agents phenotype, P_t determines their biological fitness. Once more we derive from Grove (2019) in our specification of the fitness function. The reasoning for doing so are two-folds: i) their modelling is representative of theoretical findings in prior literature, and ii) Simplicity. We define our fitness function as follows:

$$F(P_{it}, B) = 100 - c * (B - P_{it})^2 \quad (2)$$

The c here represents the cost to individual learning. The theoretical basis for which have already been discussed⁶. B represents the state of the environment. In each period the agent chooses how much of their phenotype is a result of social learning, α . We set up two variations of this model: certain and uncertain. The certain variant has a fixed B each period⁷. Changing the parameter B should not have any qualitative changes in the dynamics of the search process. Note that the optimisation function is concave in P_{it} . In the rational expectations equilibrium, the subjects would want to ideally meet the following first order condition:

$$B = P_{it} = \alpha_{it}X_i(t-1) + (1 - \alpha_{it})X_{it} \quad (3)$$

In our framework, however, agents adopt a Genetic Algorithm based search process. So they are not assumed to have enough information to arrive at a rational equilibrium solution immediately. However, given the simplicity of

⁶See Mcelreath et al. (2008)

⁷We set $B=30$ for our simulations.

the payoff function we estimate that a small number of periods ($t=30$) would be sufficient for the algorithm to find the optima. Given the simplicity of the first order conditions, there are a few limitations to this analysis. Having a more complicated payoff function could allow us to model what would happen under multiple optima points. Under such a pay-off function the trade-off between individual search and social learning would be more pronounced. Despite the simplicity of the model, it does allow us to see how factors like information cost can affect the agent’s preferred learning strategy.

We further introduce a little noise in the environment parameter to introduce a dynamic environment into our analysis. In this variant, the parameter B is drawn randomly from a normal distribution every period. Thus introducing significant noise into the environment. Under this framework the agents would be required to maximize an expected pay-off function similar to the one shown above. Formally we define the agent’s problem in this new uncertain environment as follows:

$$\max F(P_{it}, B) | E(B_t) = 100 - c * (E(B_t) - P_{it})^2 \quad (4)$$

Given the greater uncertainty surrounding the environment we would expect a lower preference towards social learning strategies, α . Barrett et al. (2019) have made similar remarks in their works. We study the evolution of α throughout the simulation under both variants of the model. We also look at the effect of changing c on α . There is a clear consensus in prior literature that an increase in the noisiness surrounding information acquired through individual learning could increase a preference towards α . In the fol-

lowing sections we move onto discussions about the computational approach undertaken to simulate our model.

4. Genetic Algorithm

Genetic algorithms have paved their way into social science research as a useful tool for providing open form solutions of problems that are analytically more challenging to solve. Pioneered by Holland (2012), the algorithm has found its application in numerous problems requiring search algorithms. The algorithm is based on evolutionary theory. It identifies each agent within the model using a set of binary strings that are akin to chromosomes. The chromosomes carry information about the strategy played by the agent in each period. These chromosomes undergo a wide range of genetic operations each period which makes these operators the engine block of the algorithm. For our simulation we only adopt two genetic operators; reproduction and crossover. Axelrod (1980) shows that having a simpler version of the algorithm has no qualitative impact on the convergence of the algorithm to an optima. It could be argued that the convergence simply takes longer and is noisier upon approaching close to the optima. We briefly discuss the operations and other specifications of the algorithm in the following subsections.

4.1. Information encoding

Each agent in the environment is initialised by the random generation of a set of 10 strategies or chromosomes. Essentially these are represented as strings of binary bits. Each agent is therefore represented by a set of 10 such chromosomes or strategies. We then initialise the environment to have six such agents. The agents are able to observe their own strategy space but not

those of the other agents. This is done to rule out the modelling of social learning within the algorithm. An Individual Evolutionary Learning model was therefore deemed appropriate⁸. Each agent is defined by a binary string of length, $l=40$. The first 20 bits encode information regarding the history of the strategy space. They are used to determine the values of X_{it} and $X_i(t-1)$. The second 20 bits encode information regarding the preference for reliance on socially learnt strategies, α ⁹. The values for α are normalized such that $\alpha \in (0, 1)$. We use the following decoding process for α :

$$\alpha_{it} = \sum_{j=21}^{40} a_{it}^j \frac{1}{2^{40} - 1} \quad (5)$$

4.2. Reproduction

After the end of each period the agents update their information set (binary strings). This updating is done in two steps, the first of which involves reproduction. Reproduction is conducted using a roulette wheel approach. This simply means that chromosomes that yield a phenotype with higher biological fitness are more likely to be replicated in the next period. This is done by calculating the fitness of each chromosome after the end of each period. Then each chromosome is assigned a probability π of being reproduced

⁸The use of Genetic algorithms can be categorised under two variant frameworks: Individual Evolutionary Learning or social learning. The latter category allows each agent to observe not only the information over their strategy space but over the entire strategy space. This specification is avoided because we already model the trade off between social and individual learning from the specification of our pay-off function. So in order to prevent entangling the two effects we opt for the IEL variant of GA.

⁹A similar approach to decoding information on dual choices is undertaken in Anufriev et al. (2013) and Arifovic et al. (1997).

in the next period. Whereby, the probability is determined by:

$$\pi_i = \frac{F_i(P_{it}, B)}{\sum_{i=1}^n F_i(P_{it}, B)} \quad (6)$$

4.3. Crossover

After n agents are replicated from the previous period so as to keep a constant population size, we conduct crossover of the strings. This essentially involves splitting the string in half and interchanging the halves with other strings in the same set. More specifically, two strings would be selected at random from an individual's list of strings. With some probability, say p^{10} , the strings will be split in half and exchange on half of their chromosomes. These means that the strategies formed in the next period are somewhat a result of genetic information carried down from their parent chromosomes.

These two simple operations combined complete our search algorithm¹¹. The genetic algorithm is undertaken under various specifications of the cost parameter and under two specifications of the environment parameter. We present a categorical analysis of our results in the next section. We also check for robustness of the model under different specifications of c and B which are the search cost and environment parameters in our model.

5. Results

Following Grove (2019) we adopt parameters values for $c = \{0.1, 0.5, 0.9\}$. We use $c=0.1$ as the base case to compare the evolution of α under a

¹⁰We keep the value of $p=0.6$ throughout all of our simulations.

¹¹A detailed account of the simulation procedure including the python codes are included as an addendum to this document.

fixed environment setting compared to the uncertain environment setting¹². We look at the evolution of α in 30 period simulation. The simulations are run for 30 times to account for randomness in the initialisation process. We produce summary statistics of the α parameter under both settings from these thirty simulations.

Table 1: Table 1: Summary Statistics

Environment	Mean, α	Variance, α	n
Certain	0.9	0.0174	30
Uncertain	0.9	0.017	30

As the summary statistics show there is surprisingly no change in the mean of α despite introducing uncertainty in the environment. This is contradictory to assertions in the literature pertaining to the effect of a changing environment on the agent’s reliance on social learning. It seems that changing the environment in each period does not make much of a difference to the agent’s reliance on social learning strategies. There is also very little difference in the variance of α across the two groups of experiments.

One possible explanation for this is the oversimplification of the pay-off process. A more complicated pay-off function may yield more interesting dynamics. Expecially, having one with multiple equilibria could help identify another cause for preference for social learning strategies close to the equilibrium. It is reasonable to think that the agents will have a higher preference

¹²B is set to 30 in the fixed environment setting. Variation in this parameter did not have qualitative changes on our findings.

for social learning strategies i.e. a higher value of α when the pay-off function is close to an equilibrium. Reallocating biological resources into individual learning via costly searches may not be rational to an individual close to an optimum point in their pay-off function. However, the existence of a second, possibly higher equilibrium designed into the pay-off function can help illustrate a more realistic and complex dynamic in the long-term evolution of preference towards social learning strategies.

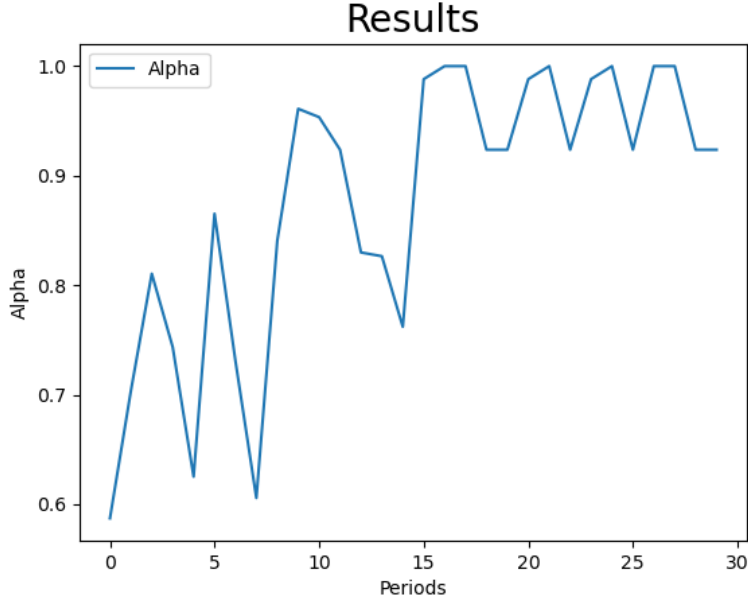


Figure 1: The Evolution of α under Uncertain Environment

This notion is somewhat apparent from the plots of the mean value of α in our population throughout the simulation. As expected, we see a lower reliance on social learning strategies in the initial phases of the simulation. The agents have been just initialised into the environment and must incur some cost initially to expand their strategy sets. In fact, we see a high vari-

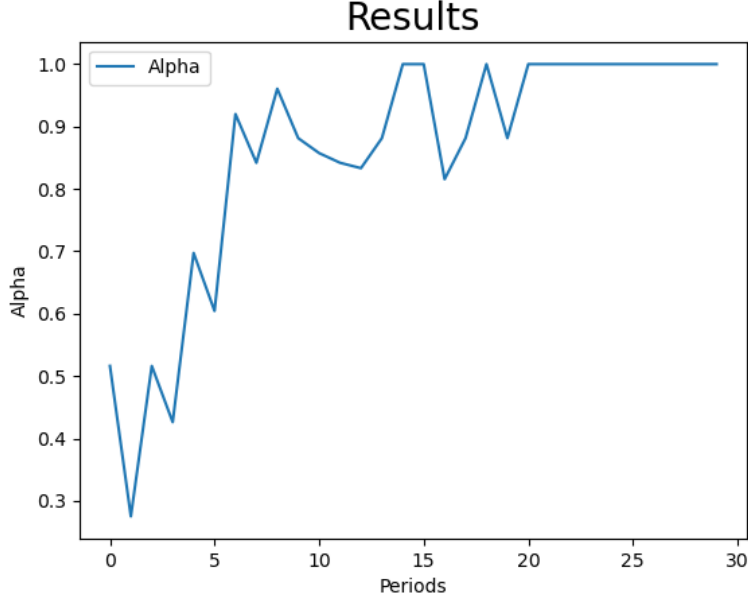


Figure 2: The Evolution of α under Fixed Environment

ance in α in the initial periods as the agents experiment to find the optimal allocation. Reliance on past strategies is initially emphasized followed by a fall in α suggesting a greater reliance on individual learning strategies. This back and forth continues until the algorithm finally converges to the optimal point in the pay-off function. Naturally, the reliance on social learning strategies increase at this point and go very close to 1. The reasoning for a higher preference towards social learning strategies under close proximity to an equilibrium should be clear from the above discussion. This finding in our simulation is consistent with the literature. Duffy et al. (2019) find similar patterns of strategy formation in their sequential choice experiments. Another interesting point of observation is that the algorithm does not converge to an equilibrium under the uncertain environment. This is intuitive

because we are introducing a new environment everytime causing the agents to constantly update their information. Hence, in the uncertain environment base case the α does not approach as close to 1 as in the fixed environment specification.

We also test the robustness of our results under different search cost specifications. The aforementioned considers the base case with $c=0.1$. In the following simulations we see the effect of an increase in c for $c= \{0.5, 0.9\}$ for both variants of our model (certain an uncertain). We first present the case for the certain environment with $B=30$.

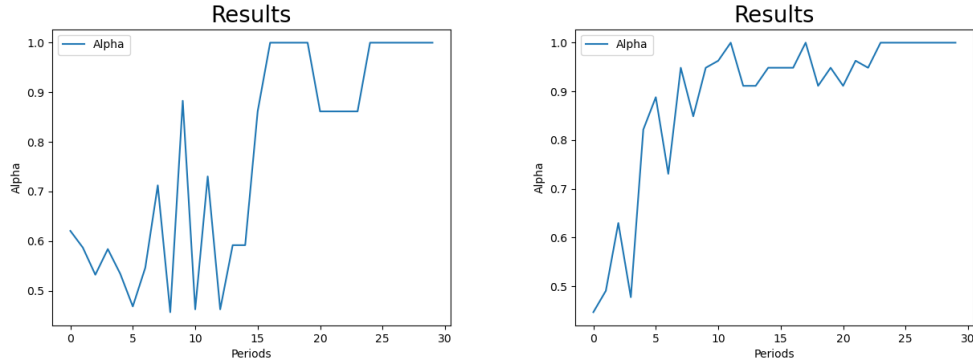


Figure 3: The effect of changing c on α in a fixed environment.

The right hand side picture shows the case where the cost of individual learning is shifted up to 0.9 from 0.5. The increased cost of information search makes the convergence process longer with a higher proportion of the population with low α for a prolonged period of the simulation. In comparison, when c is set to 0,5 the convergence process is faster. We see a smoother climb in preference towards social learning strategies when the costs associated with individual information search increases. This is in line with

the findings of the literature, and suggests that our model accurately captures the trade-off between social learning and individual learning strategies when there are costs associated with individual learning. This finding is consistent

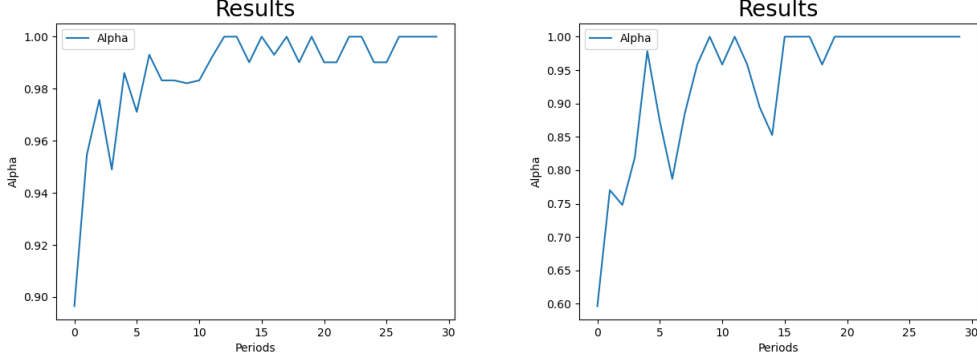


Figure 4: The effect of changing c on α in an uncertain environment.

across different settings of the environment parameter. Even in the uncertain variant of our model, increasing c from 0.5 to 0.9 leads to higher variance in the proportion of social learning strategies played. This is apparent from the figure on the right which shows higher variance in α throughout the simulation compared to the figure on the left. Again, this reiterates the notion that an increase in cost or noise associated with individual learning strategies can generate a preference towards social learning.

6. Conclusion and Limitations

Prior to re-iterating the stylized findings of the paper, we would like to address some of its many limitations. Firstly, the pay-off function is clearly an oversimplification of a more complex phenomena. It would be more interesting to see how the preference for reliance on social learning strategies

evolve under a multiple equilibria model. This could be an avenue for further research. Integrating a more representative pay-off function will allow us to better model the subtle nuance in the trade-off faced by the agent between exploring new strategies and exploiting existing ones. A further limitation of the paper is the inability to conduct an appropriate number of robustness checks. Although the literature suggests changing the environment parameter should not have any qualitative effect on the overall results, this is something that needs to be further verified.

Despite the obvious limitations of the model, there are certain stylized findings that are concurrent with the current literature. Especially, we find evidence to corroborate those of Duffy et al. (2019), van Schaik and Burkart (2011) and Galef Jr and Whiskin (2008). Social learning strategies are clearly evolutionarily optimal under close proximity to the equilibrium. This is apparent from the trend of α to converge towards 1 as the algorithm closes in on the optimal phenotype. Similar evidence regarding the dynamic of preference evolution for social learning strategies is observed by Duffy et al. (2019). This trend also corroborates the theories underlying the cultural intelligence hypothesis. There is clearly evolutionary advantage to having a rich history of low-cost past strategies to rely on. The paper however, does not find evidence of a rapidly changing environment lowering the preference for social learning strategies. This is in contradiction with Barrett et al. (2019). Future research endeavors could be directed towards a more sophisticated specification of the pay-off function to yield more insights.

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