

The Effect of Noise on the Emergence of Continuous Norms and its Evolutionary Dynamics

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Abstract

We examine the effect of noise on societies of agents using an agent-based model of evolutionary norm emergence. Generally, we see that noisy societies are more selfish, smaller and discontent, and are caught in rounds of perpetual punishment preventing them from flourishing. Surprisingly, despite the detrimental effect of noise on the population, it does not seem to evolve away. In fact, in some cases it seems the level of noise increases. We carry out further analysis and provide reasons for why this might be the case. Furthermore, we claim that our framework that evolves the noise/ambiguity of norms is a new way to model the tight/loose framework of norms, suggesting that despite ambiguous norms' detrimental effect on society, evolution does not favour clarity.

Introduction

The social world is replete with norms, an important aspect of organising societies. Social norms reduce the degrees of freedom in the actions of individuals, making them more predictable and stabilising societies (FeldmanHall and Shenhav, 2019). Norms also enable unrelated agents to manage shared resources (Mathew et al., 2013), thereby extending cooperation beyond genetic relatives (Richerson et al., 2016).

Norm emergence is usually studied with discrete behaviours. Game theory tends to consider moral behaviour to be composed of discrete actions: cooperate and defect (Axelrod, 1986), hawk and dove (Smith, 1982), stag and hare (Skyrms, 2003). Other examples of discrete norms include political party affiliation, coordinating or not coordinating (Lewis, 1969; McElreath et al., 2003) or adopting a given behaviour e.g. a possession norm (Epstein and Axtell, 1996; Flentge et al., 2001). We know, however, that norms are not always this discrete, and a large number of norms exist on a continuous spectrum of behaviour, e.g. what amount is acceptable to take from a shared resource, how fast you walk, how close you stand next to someone during a conversation (Kelly and Setman, 2021). These have received much less attention in terms of modelling (Le and Boyd, 2007), with the exception of continuous opinions as modelled in the closely related field of opinion dynamics (Flache et al., 2017).

Previous work using continuous behaviour includes continuous iterated prisoners dilemma (Le and Boyd, 2007) (on a scale of 0 complete defection, to 1, cooperation). In general, cooperation in continuous dilemmas is less stable and it is harder for cooperation to invade a population of defectors (Le and Boyd, 2007). Bendor et al. (1991), investigated how noise affected the success of fixed strategies in a continuous prisoners dilemma. They showed that populations of generous strategies were more successful because generous strategies avoided spiraling into rounds of mutual recrimination in noisy environments. Going beyond continuous game theory, Aubert-Kato et al. (2015) investigated the emergence of frugal and greedy behaviours in an embodied version of a dilemma where agents varied in how long they exploited a food source – the longer it exploits the food source, the more selfish the agent is. Michaeli and Spiro (2015) showed how “liberal” and “conservative” punishment regimes can affect the polarisation of a continuous opinion. Further, previous work on iterated prisoners dilemma by Ashlock et al. (2006) showed that even small differences in implementation, e.g. representation choice, can lead to significantly different dynamics.

We intend to combine these previous elements together to investigate the effects of noise on the emergence of continuous social norms. We investigate this in an evolutionary agent-based simulation, comparing agent societies with deterministic and probabilistic behaviours to see if noise significantly changes the dynamics of the society, i.e. norm emergence and other properties of agent societies. To achieve this, we evolve three continuous norms. Uniquely, we also evolve the level of noise on each of these properties. This allows us to investigate the effect of noise on a continuous model of norm emergence, which is of use to modelers considering whether or not to include noise in their models. Further, by making the amount of noise a variable that is available to evolution, it allows us to study the evolutionary dynamics of noise.

We define criteria for norm emergence in a continuous system and show that our deterministic societies obey these

criteria. We find that deterministic societies tend to be less selfish, less hypocritical and less discontented, with agents sharing resources more effectively and sanctioning each other less. In contrast, noisy societies tend to fall into perpetual punishment of each other despite the abundance of resources.

This begs the question, if noise is detrimental to the agent society, why does it not evolve away? We show that there does not seem to be an evolutionary pressure to eliminate noise and offer some reasons as to why this may be the case. Further, we suggest our model offers some insight into thinking about the evolution of loose and tight societies. The tightness-looseness framework looks at culture in terms of the strength of their cultural norms (number and clarity) and strength of punishment when a norm is violated. Tight cultures have stronger norms and punishments and loose cultures have more vague norms with less harsh punishments. This framework provides insights into the function of norms, with cultures tightening in response to threats, making them better at dealing with them. Our model expands the existing work by considering the noise inherent in looser societies that have more vague or ambiguous social norms (Gelfand et al., 2006; Roos et al., 2015; Pan et al., 2021).

Model and Experiments

The following section introduces a multi-agent model we developed to study the effect additive noise has on continuous norm emergence. We study two experimental conditions in the model. In the deterministic case, the behavior of each agent is defined by three internal, continuous variables (Bite Size (B), Sanction Threshold (T) and Sanction Strength (S)). In the probabilistic case, we add Gaussian noise to those variables each time they are used to determine behavior. The strength (variance) of this added noise is defined for each of the three internal values by another three agent-specific values, respectively - i.e. BN, TN and SN. The simulation can be separated into different steps, as visualized in Fig. 1, which are defined as follows:

Initialisation

At the beginning of the simulation, we create 100 agents and set the resource level to 1000 units. Each agent's internal values for B, S and T are initialized to uniformly random values between 0.0 and 1.0. For the probabilistic model, each agent's noise values (BN, TN and SN) are initialized between 0.0 and 0.5. Each agent's energy level is set to 10. After initialization, the simulation proceeds in rounds. Each round has a different, randomized order of all agents, and each of the following steps is performed in that order.

Eat

When it is their turn, each agent tries to consume resources according to their Bite Size (B). This value is added to

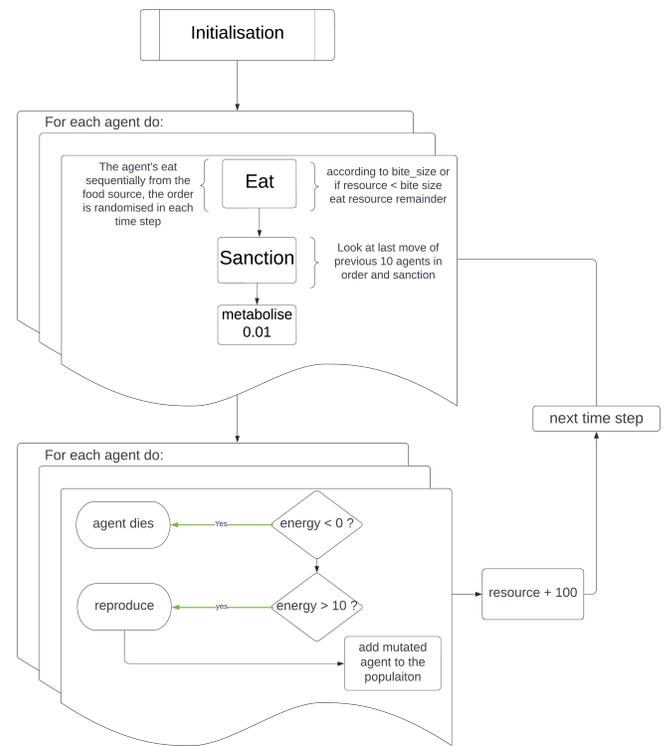


Figure 1: Flow diagram describing the stages of the agent-based simulation.

their internal energy and removed from the global resource level. If there are no resources left, the agent gets no energy. The higher the value, the more greedy/selfish the agent is compared to other agents. If all agents eat at a higher Bite Size, the environment will not be able to support as many agents; thereby exhibiting 'tragedy of the commons' dynamics (Hardin, 1968).

Sanction

During their turn, each agent can observe the actually consumed resources of the 10 previous agents. Each agent checks if the previous agents ate more than its own internal Sanctions Threshold (T); if so, it sanctions them. In other words, T is the amount of deviance an agent tolerates before punishing another agent, i.e. what an agent finds acceptable. Sanctioning means the agent reduces the other agent's internal energy by its own Sanction Strength (S), and it also pays a sanctioning cost of $0.1 * S$, which is subtracted from its own energy level.

Metabolise

Each agent has their energy level reduced by 0.01 during each round.

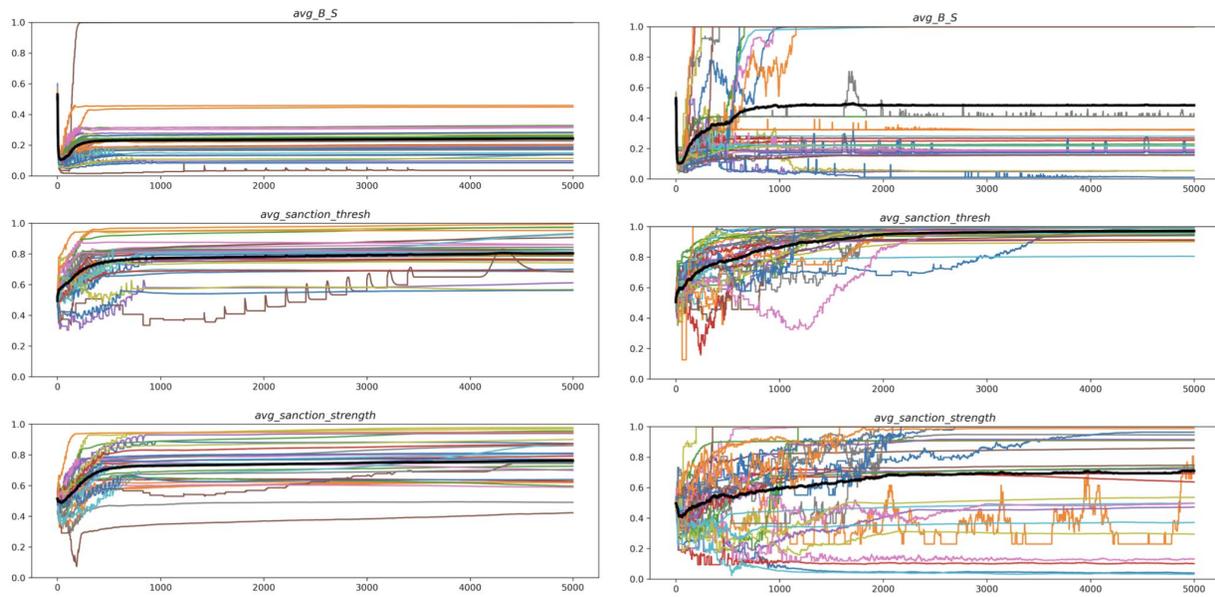


Figure 2: The average value of each trait in the population plotted over time. Deterministic (left) and probabilistic (right). Individual runs are plotted as coloured lines and the average of those runs is plotted as a black line. $N = 34$ per condition.

Death and Reproduction

After those steps, the simulation checks if any agents have an energy level lower than 0.0, in which case they are removed from the simulation. Then any agent with an energy level larger than 10 gets to reproduce. Reproduction means we generate a copy of the agent, with the same 3 or 6 internal values, mutated with a 0.1 chance by adding Gaussian noise with 0 mean and 0.1 variance to each of those values. The energy of the child and parent are both set at half the parent's prior energy level. Before the next round starts, we add 100 units of resources to the resource level.

Creating Probabilistic Behaviour

To create the probabilistic behaviour, we used a Gaussian function each time the agent consumed from the shared resource or punished another agent. Using their value and accompanying standard deviation (noise parameter) to create a value for the amount of food eaten B , how tolerant they are T and how harshly they punish S , e.g. for each instance of sanctions we select the strength from a normal distribution with a mean of S and a standard deviation of SN . This added noise can be interpreted either as behavioral or perceptual error.

Implementation Choices

The evolutionary dynamics in this simulation are created by differential reproduction, rather than by defining an explicit fitness function and selection process. Since the order agents

eat and sanction each other is sequential, it means agents at the front of the queue have an advantage, as they get to consume from the resource first. Conversely, being last in the queue also has an advantage as there is no one behind the agent to sanction them. To minimise the impact of these asymmetries on the results, we randomise this order in each round. We limit the initial values for the noise values to $[0.0, 0.5]$, because some initial simulation with the full range resulted in very volatile dynamics that were hard to analyze. But after initialization, it is possible for the noise parameters to have any value between 0.0 and 1.0 so they can adapt in that direction. We explored further parameter settings not reported here (varied agent metabolism, cost of sanctions), which produced results similar to those in this paper. Note that the deterministic condition can be seen as a special case of the probabilistic condition, where the three noise parameters are very close to 0 for all agents.

Results

Continuous Norm Emergence

First we want to answer the questions, is this a model for the emergence of continuous norms? Usually in discrete models there is an arbitrary threshold, such as 80 percent of the population must possess that behaviour for it to be considered a norm (Savarimuthu and Cranefield (2011)). Since our behaviours are continuous, and its not clear what it would mean for two agents to have the same behaviour, we define criteria on how to assess norm emergence in a continuous context.

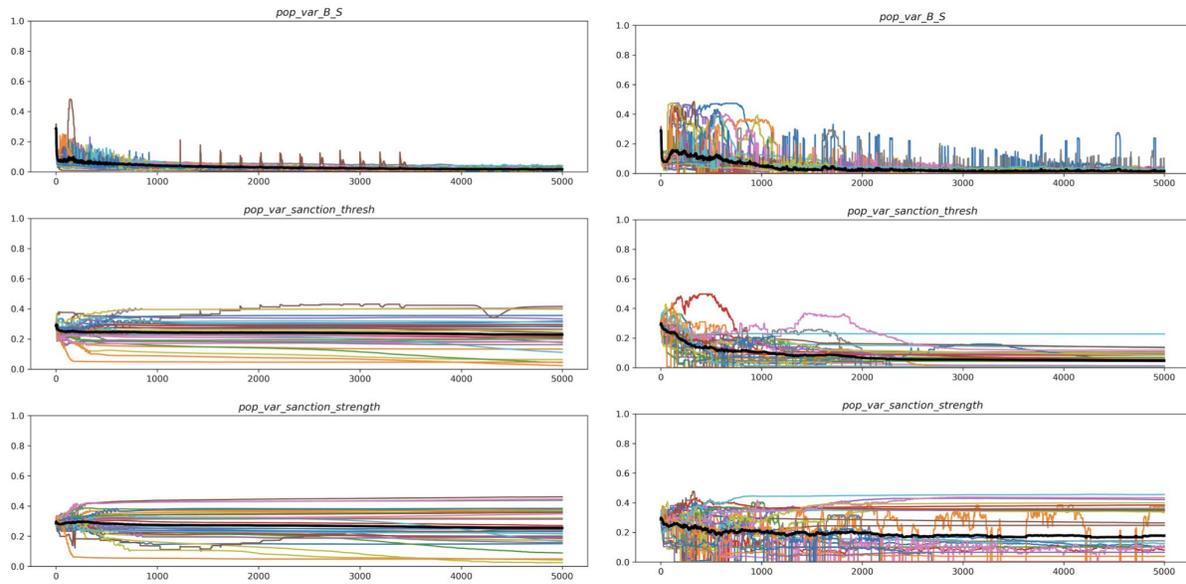


Figure 3: The population-level variance (the variance of a trait in each population) of each trait plotted over time. Deterministic (left) and probabilistic (right). Individual runs are plotted as coloured lines and the average of those runs is plotted as a black line. $N = 34$ per condition.

1. The behaviour converges and stabilises: Do traits decrease terms in variance across the population from where they began, and do the average behaviours stabilise? This would be indicated by a decreasing value for the variance of a given behaviour across the agent population, and a lack of change of the average behaviour over time.
2. The behaviour the population stabilises at is arbitrary across runs to a certain extent: This criterion ensures the resultant behaviour is not fully due to environmental scaffolding, meaning when the behaviour is the only rational/viable action given the environmental constraints, e.g. a population level preference for walking over a bridge as opposed to walking across lava would not be considered a norm (Westra and Andrews, 2022). This would be indicated by repeated simulations stabilizing at different average values. Note that this requires some level of randomness in the simulation, with different seeds.

Further to our stipulations, we clarify that we are talking about norms under the general definition of normative regularities: "A socially maintained pattern of behavioral conformity within a community." (Westra and Andrews, 2022). We take this definition rather than a rule-based one, which requires higher cognitive capacities such as language (required to express the rule) (Kelly and Setman, 2021). Further, we think it is a wider framework that encompasses a broader range of phenomena that are of interest. This

permissive of "bottom-up" approach may help us reveal the building blocks of normative cognition (Westra and Andrews, 2022; de Waal and Ferrari, 2010). In Fig. 2, we see that in our deterministic simulation, after about 200 tics, all agent traits manage to settle on a particular value. This value is arbitrary to a certain extent with different runs settling at different values. This is important as it means that the behaviour is indeed a norm and not just a product of environmental scaffolding, i.e. the only rational action given the environmental circumstances (Westra and Andrews, 2022). In the probabilistic cases, it seems that norms are a lot more volatile, with average values in flux. Further, if we look at the population level variances of each trait in Fig. 3 we see that Bite Size converges onto a much lower level than it began, thereby satisfying our criteria for norm emergence as the population converges on a shared behaviour. On the other hand, the population level variance of Sanction Threshold and Sanction Strength does not always decrease, so it is harder to make a case for the population to converge on a norm for the latter two traits. This effect doesn't happen as much in the noisy case (Fig. 3), although there is some convergence for Sanction Threshold and Sanction Strength. However, this could be explained by the fact that probabilistic populations tend to have much lower populations than deterministic ones (Fig. 4), which could be decreasing the variance through random drift.

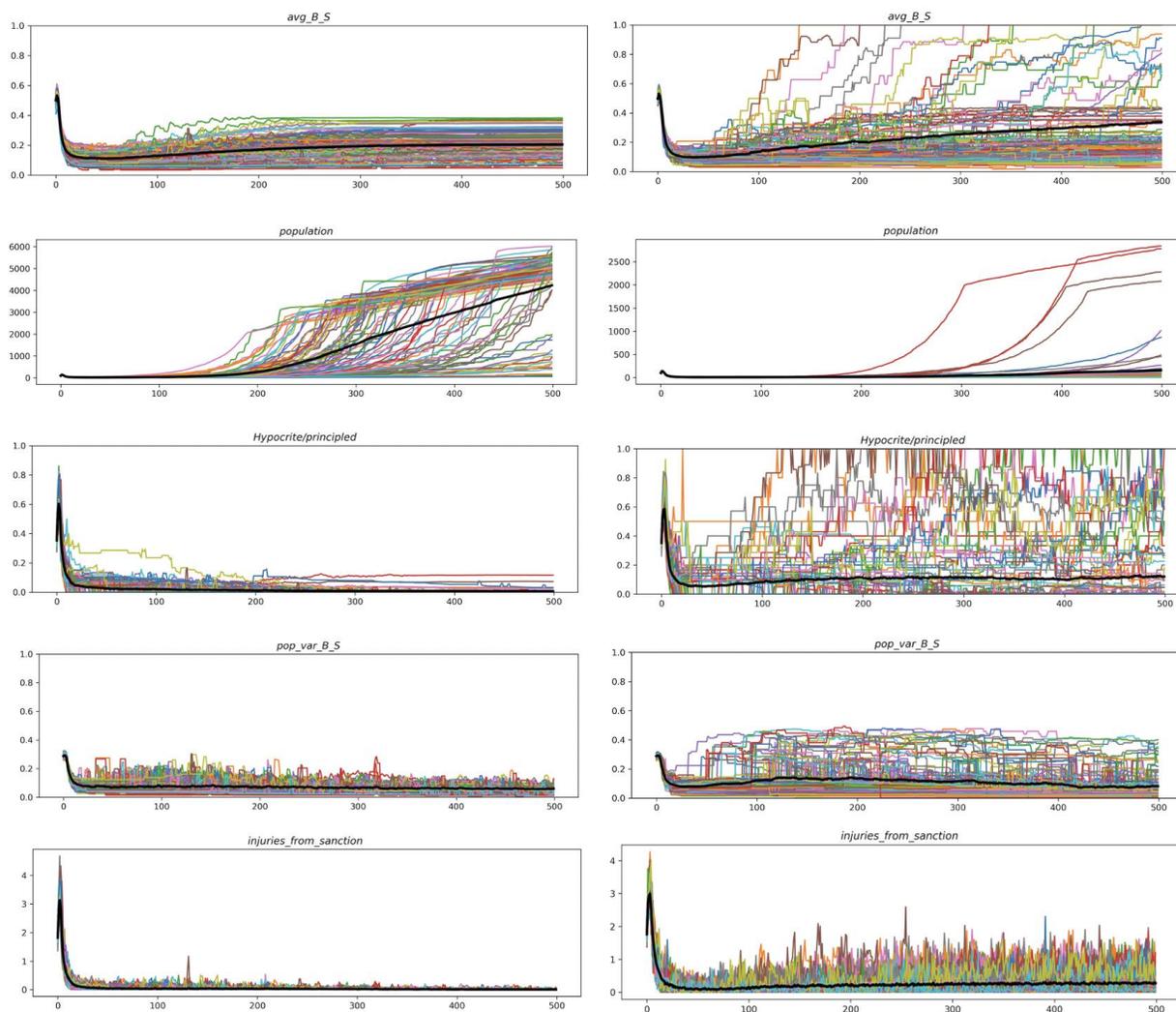


Figure 4: Various agent and population properties plotted over time. Deterministic (left) and probabilistic (right). Individual runs are plotted as coloured lines and the average of those runs is plotted as a black line. $N = 100$ per condition.

Comparison Deterministic vs. Probabilistic Model

Probabilistic agent societies are generally more selfish and have less stable cooperation. Fig. 4 shows that deterministic societies tend to have lower Bite Sizes than probabilistic ones, meaning the societies tend to be less selfish as they are all consuming less. Further, the norm seems to be more stable in the deterministic condition, with many cases in the probabilistic condition that initially settled on low Bite Sizes breaking out into higher Bite Sizes. Particularly striking is that in 100 runs none of the deterministic runs broke away, suggesting very stable norms in the deterministic population and volatile in the noisy populations. Further, when this experiment was done with an initial noise range of $[0.0, 1.0]$ as opposed to $[0.0, 0.5]$, the average value of Bite Size went up to 0.9, indicating very high levels of selfishness.

Values for the other two norm traits (Sanction Threshold and Sanction Strength) are comparable between probabilistic and deterministic societies, but as with Bite Size, the runs in the probabilistic version are more volatile (Fig. 2). The probabilistic populations are dramatically smaller (Fig. 4), with populations of 20 compared to thousands in the deterministic case. Only a handful of the probabilistic populations manage to reach comparable population levels to the deterministic populations. Probabilistic societies are more hypocritical (Fig. 4). We defined hypocrisy as an agents sanction threshold being lower than its own Bite Size ($T_{self} > B_{self}$). After an initial increase at the beginning of the simulation, both deterministic and probabilistic populations see a sharp decrease. However, rates of hypocrisy are much lower in the deterministic

case (around 0) compared to hypocrites in the probabilistic case (around 0.05), and the noisy runs are generally more volatile, with numerous runs breaking out into high numbers of hypocrites.

Initially, probabilistic and deterministic societies also have similar levels of norm convergence as measured by trait variance decreasing initially and staying at around 0.1. However, as in Fig. 2, this level of convergence is less stable in the probabilistic condition. Further, since the populations are much smaller in the probabilistic condition, this may bias the population level variance metric, so we should not read too much into this result. Further, the small populations mean genetic/cultural drift effects could overpower subtle selection pressures. Despite the small populations, however, there is still a significant amount of births/deaths (data not shown here), suggesting selection is still happening. To address the effects of small populations in the future, we will have a fixed population with replacement instead of a dynamic one. But for now, since we are interested in seeing the effect on noise on the size of the populations as well, we will keep it as is.

Strangely, the reason for low populations in the probabilistic population is not a lack of resources. To see the real reason, we look at the amount of energy lost due to punishment of the agents (Fig. 4). This plot shows that the amount of energy was lost either as a result of damage from sanctions or cost of executing sanctions. In the deterministic case, we see a spike in sanctions at the onset if the simulation as agents punish each other due to the diversity of norms. The society then converges toward a norm as the sanctioning decreases. In the probabilistic case, it seems the societies do not adequately manage to converge most of the time, resulting in this period of adjustment never ending, leading to discontented society marred by perpetual punishment. This may be the reason agents raise their Bite Size in order to better protect themselves against punishment; in a high-noise society has hypocrites, you will likely be punished anyway, so there is no rational reason to be generous and have a low bite size. It is important here to mention our simulation is not a case of limited resources; in fact, the regrowth rate of the simulation is quite high to assess the dynamics of noise in plentiful conditions.

In conclusion, probabilistic populations are more selfish, hypocritical, discontented and less stable while the deterministic populations managing to reach drastically higher populations with the same amount of resources.

Noise Evolution

Given that noise in our model seems to be detrimental to a society overall, and noting that the deterministic model is just a special case of the probabilistic model, we would expect that our models evolve away the noise. But if we look at the development of the average value for the three added noise parameters, we do not see a decrease of noise (Fig.

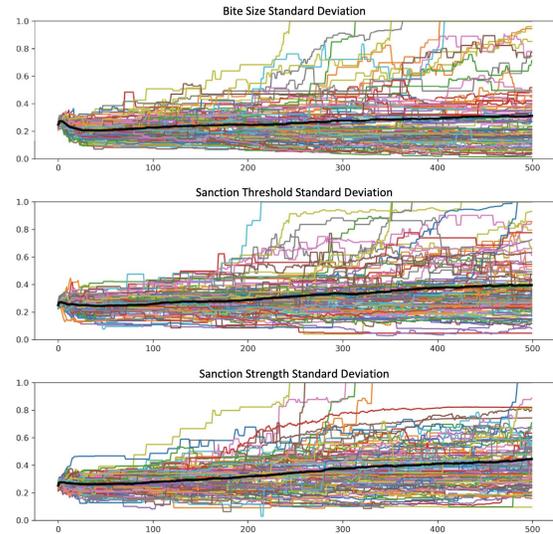


Figure 5: The average standard deviation (noise) for each trait plotted over time. Individual runs are plotted as coloured lines and the average of those runs is plotted as a black line. $N = 100$ per condition.

5). On the contrary, if we just look at the first 500 steps, the average noise seems to slowly increase. This could in part be explained by a random walk, since we initialize between $[0.0, 0.5]$ but allow for noise to evolve to the full range of $[0.0, 1.0]$. If there was no evolutionary pressure, we would expect the noise parameters to drift towards 0.5.

To investigate the evolutionary dynamics of noise, we looked at how the standard deviation evolved over time (Fig. 5). We see that average noise apart from small deviations does not really seem to increase. With the individual runs looking like random walks and the average not really changing. To further investigate why this is happening and to make sure this lack of evolution is not due to the shortness of the runs, we did the following. We first ran a sample of 34 runs for each condition for 5000 time steps (10x longer than previous experiments) and then compared noisy runs that were successful (i.e. reach large populations larger than 5000, which is comparable to the deterministic case) with those that were not successful (i.e. where the population collapse or stayed at low population numbers).

Interpreting the Evolution of Noise

In the longer runs, we see that noise seems to slightly increase for Bite Size for all runs Fig. 6 (left panels). But if we look at only the successful runs (right panels), it seems that on average they don't really change in terms of their value over time. For some of the runs, this might not be so much due to evolutionary adaptation, but the fact that the runs started with low noise to begin with and happened to be better at surviving. This being said, a minor proportion of

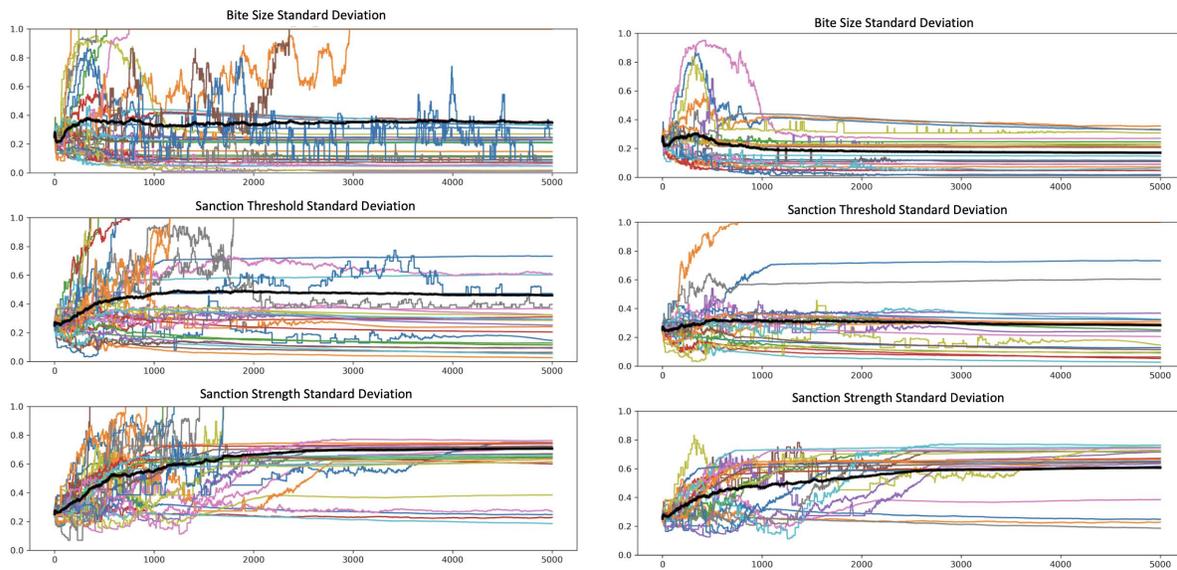


Figure 6: The average standard deviation (noise) for each trait plotted over time. All runs (left) and only runs with *populations* > 5000 (right). Individual runs are plotted as coloured lines and the average of those runs is plotted as a black line. $N = 34$ per condition.

successful runs had an initial increase in noise but eventually settled at low noise values. It seems then that for Bite Size, successful runs (those that reach higher populations) are runs that, by chance, started at the low noise levels.

If we look at the noise for Sanction Threshold (tolerance) (TN), we see a similar pattern: a slight increase in noise overall if we look at all of the runs but the majority of the successful runs start at low noise and remain there. So although the graphs show that we could reduce noise by selecting populations by their overall performance, noise level does not seem to decrease when selection occurs on a per agent basis.

In contrast to the other two traits, Sanction Strength noise (SN) seems to increase in both successful and unsuccessful runs, in spite of the fact that noise is initialised at $[0, 0.5]$ (Fig. 6). Specifically, there seems to be a region between 0.6 and 0.8 where the most successful runs seem to settle, with unsuccessful runs above and below this region. One could interpret this as being a selection pressure favouring an intermediate level of Sanction Strength noise, however more experiments with runs starting at a wider range of noise would be needed to conform this.

Taken together, this results seem to suggest that although noise makes agent populations less successful, there doesn't seem to be an evolutionary process that reduces noise, in fact, in the case of Sanction Strength, evolution may increase noise.

Discussion

We present a model of continuous norm emergence to show the effects of noise on the dynamics of norm emergence and the simulation more generally.

We first showed that deterministic societies satisfy our criteria for norm emergence:

- 1: That they converge on behaviours compared to the start of the simulation; and
- 2: That the norm is somewhat arbitrary, meaning not the only rational action given the circumstances i.e. environmental scaffolding (Westra and Andrews, 2022).

Second, we showed that deterministic societies compared to noisy ones are: more able to settle on norms, distribute resources effectively (altruism), less hypocritical, less discontent and are more stable in these properties over time. In contrast, noisy societies do not prosper because they have high levels of sanctioning not seen in deterministic societies, falling into rounds of perpetual punishment. This result goes against the "mad man theory" hypothesis, where an adversary in a negotiation is more likely to stand down if they think their opponent (in our simulation, the agent sanctioning) is unpredictable to avoid provoking them (McManus (2019)). In our simulation, it appears that noisy punishment only seems to incentivise agents to increase their provoking behavior (breaking norms by increasing Bite Size). This occurs because they will be punished whether they obey a norm or not, so they might as well consume as much as they can to increase their chances of survival.

Although, the detrimental effects of noisy sanctions may be due to the fact that both the punishment behaviours (S and T) and eating behaviour (B) are noisy, further analysis by adding noise to only one of the behaviours e.g. B or T would be needed to confirm this.

The widespread instability of noisy societies raised the question: if noise is detrimental, wouldn't it evolve away? Through further analysis, we showed that although populations with low levels of noise ended up being more successful (reaching higher populations), there wasn't an evolutionary trend toward reducing noise, in fact in some cases there seemed to be an evolutionary pressure to increase noise.

We offer some explanations why this may be happening. Firstly, for noise to be selected against there might need be group selection, as deterministic societies tend to be much larger, they would be able to out compete smaller noisy groups. Secondly, although high levels of noise are detrimental to the group, there might be a benefit to the individual of having noise; perhaps it enables them to avoid punishments. Further, one agent lowering their noise would not necessarily benefit them enough to dominate the population if the rest of society still has high levels of noise.

A further contribution of this paper is that it may offer a way to model/think about the evolution of cultural tightness/looseness (Gelfand et al., 2006). Which is defined as 1. strength of sanctioning (tolerance to deviance from norms) and 2. strength of social norms (number and clarity). Tight cultures have stronger norms and punishments and loose cultures have vaguer norms with less harsh punishments (Gelfand et al., 2006; Roos et al., 2015). We refine 1. by differentiating between tolerance to deviation (i.e. sanction threshold) and also the strength of punishment when someone deviates (i.e. sanction strength). Further, our model could be a new way to model the evolution of clarity of social norms using noise (2). Finally, computer models studying tightness and looseness assume discrete behaviours, we relax this assumption by grounding our study in a continuous modelling framework (Pan et al., 2021). Taking this lens on our simulation, we could claim that the clarity of norms (tightness) can't be evolved despite there being selective pressure against it. This is a peculiar finding, as it would imply although societies with vague rules are at a disadvantage, ambiguity persists.

Future Work

In our future work we would like add the following extensions. Currently the regrowth rate of the shared resource is static. We could vary this and make the resource growth dynamic by having "seasons" and see the resultant dynamics. Further, we only studied vertical cultural transmission but didn't include horizontal transmission, where individuals in the same generation copy each other's strategies. In contrast to other models of tightness and

looseness, our model has three norms instead of one, we could add more norms and analyse the interplay between the "tightness" and "looseness" of different norms. Finally, to further study the evolutionary dynamics of noise; we should compare different combinations of traits with and without noise, e.g. have a noisy punishment threshold but deterministic bite size and punishment strength.

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