Socially Intelligent Genetic Agents for the Emergence of Explicit Norms

Rishabh Agrawal[1] , **Nirav Ajmeri**[2] and **Munindar P. Singh**[1]
[1]North Carolina State University
[2]University of Bristol
ragrawa3@ncsu.edu, nirav.ajmeri@bristol.ac.uk, mpsingh@ncsu.edu

Abstract

Norms help regulate a society and may be explicit (represented in some structured form by the agents) or implicit. We address the emergence of explicit norms by developing agents who provide and reason about explanations for norm violations in deciding what sanctions to produce and identifying alternative norms. These agents use a genetic algorithm to create and evolve a set of norms and reinforcement learning to learn the value of these norms. We find that applying explanations leads to norms that provide better cohesion and goal satisfaction for the agents. Our results are stable for societies with differing attitudes of generosity.

1 Introduction

Norms encourage coordination and prosocial interactions in a society [Morris-Martin *et al.*, 2019]. For example, ignoring a phone call in a meeting is a social norm that helps avoid disruption. Importantly, norms may conflict with one another and be resolved in different ways [Kollingbaum *et al.*, 2007; Santos *et al.*, 2017]. In conflict, an agent must decide which norms to follow and which to violate. For example, *picking up an urgent call* and *ignoring a call during meeting* are both norms. But if you receive an urgent call during a meeting, one or the other norm must be violated.

Where do norms come from? We consider *norm emergence* to be the decentralized evolution of norms [Morris-Martin *et al.*, 2019], driven by signaling between agents. A norm violation may result in a negative *sanction*, i.e., a scowl on the face of an attendee. If the scowl is outweighed by the benefits of picking up an urgent call, the newly emerged norm would be *ignore a call during meeting, unless it is an urgent call*. Alternatively, if the sanction is severe, the emerged norm could be *pick up an urgent call, unless you are in a meeting*.

Norms can be *implicit* (encoded in behaviors that are common in a society [Morris-Martin *et al.*, 2019]) or *explicit* (explicitly maintained and reasoned about like laws [Hohfeld, 1919; Von Wright, 1963] and regulations [Jones and Sergot, 1993; Kafalı *et al.*, 2020]). Prior work considers implicit norms for emergence and explicit norms for *propagation* or *synthesis*, where norms are centrally designed and evolved [Morales *et al.*, 2018; Morales *et al.*, 2014].

In contrast to the above, we focus on the emergence of *explicit* norms. Morris-Martin *et al.* [2019] lend support to our motivation for decentralized online synthesis of explicit norms. Ajmeri *et al.* [2018] show that sharing contextual information in case of norm violations facilitates norm emergence for implicit norms and results in increased goal satisfaction and cohesion (i.e., perception of norm compliance) by helping agents understand the context (i.e., attributes that define the circumstances) in which the norm was violated and learn contextual boundaries.

We adopt the idea of agents providing *explanations* to justify a norm violation. Explanations can help achieve mutual understanding of norms, e.g., for photo sharing [Mosca and Such, 2021]; promote user acceptance and to engender trust [Biran and Cotton, 2017]; and change people's attitudes [Ye and Johnson, 1995].

Objective. Our research seeks to understand how creating and sharing *explanations* for norm violations facilitates the emergence of norms. We develop agents who produce and reason with explanations. Explicit norms are conducive to explanations of when they are satisfied or violated. We propose a method for the emergence of explicit norms by developing agents that uses rule learning [Liu *et al.*, 2015] genetic agents. Based on the foregoing, we identify these research questions:

RQ_G (Goal) *Do societies composed of agents who provide and evaluate explanations for norm violations achieve higher goal satisfaction for their members than other societies?*

RQ_C (Cohesion) *Does providing and evaluating explanations lead to norms emerging that improve social cohesion?*

Contributions. First, we develop a socially intelligent genetic agent (SIGA) in two variants: A plain SIGA (or NSIGA) represents norms explicitly; an XSIGA in addition explains its actions and incorporates others' explanations. Second, using SIGAs, we answer both RQs positively: (1) Sharing explanations to explain actions lead to improved goal satisfaction; and (2) sharing explanations to explain actions lead to emergence of norms with increased cohesion.

2 Running Example and Solution Idea

In our model, each agent has one *primary* stakeholder, whom the agent represents, and potentially many *other* stakeholders, who are affected by the agent's actions [Ajmeri *et al.*, 2020].

We adopt a phone ringer application to explain our method. An agent is responsible for ringing the phone of its primary stakeholder (the callee) when a call is received or to keep it silent. The other stakeholders are the caller and the people in the vicinity of the callee who may be disturbed by the ringing phone. Actions available to the agent are *ring* or *ignore*. The agent decides to ring the phone or keep it silent based on the norms it follows. Agents of other stakeholders may sanction the agent if they don't agree with its action.

Suppose Alice's agent follows three norms: *always ring an urgent call*, *always ring a call from a family member*, and *ignore calls during a meeting*. Suppose Bob's agent follows the norms: *always ring an urgent call*, *ignore calls during a meeting*. Suppose Alice gets an urgent call from a family member during a meeting. Her agent assigns a value (expected reward) to each action in terms of the norms that support it. If the combined value of *always ring an urgent call* and *always ring a call from a family member* is more than the norm *ignore calls during a meeting*, it rings the phone. If Alice's agent does not explain its action, Bob's agent would assume that the only applicable norm, *ignore calls during a meeting*, was violated, and sanction Alice. If Alice presents the supporting norms, *always ring an urgent call* and *always ring a call from a family member*, they are evaluated by Bob's agent. Suppose Charlie's agent follows not *always ring a call from a family member*, but *always ring an urgent call*. If Charlie's agent assigns a higher value to *always ring an urgent call* over *ignore calls during a meeting*, it would not issue a sanction. Else, it would reject the explanation and sanction Alice, leading her agent to adjust the values of its three norms.

3 Method: Realizing a SIGA and an XSIGA

A SIGA's actions are governed by explicit norms. Norms in our conception are commitments [Singh, 2013]. A commitment is written Commitment(subject, object, *antecedent*, *consequent*). The antecedent determines when it goes in force; the consequent determines when it completes (is satisfied or violated); the subject is the agent who commits, and the object is the agent to whom it is committed. We can express *(Callee) commits to always ringing a call from a family member (Caller)* as: Commitment(Callee, Caller, callerRel = *family*, action=*ring*). Commitments are well suited for rule-based learning as rules can suggest actions which can map to commitments' consequent.

3.1 Norm Learning and Discovery

A rule-based approach to implement norms supports flexibility and ease of implementation. Each agent stores norms as rules that it learns, evaluates, and evolves. (Below, we write $\top$ for true and $\bot$ for false.) Here, the antecedents are conjunctions of key-value pairs, e.g., callerRel = family, urgent = $\top$. The consequents are actions to be taken to satisfy the norm. Thus, a norm maps to a rule of the form: IF *antecedent* THEN *consequent*.

We adapt *eXtended Learning Classifiers* (XCS), a rule learning algorithm based on reinforcement learning [Butz and Wilson, 2000; Urbanowicz and Browne, 2017], which evolves rules by learning from rewards obtained from the environment in response to actions. This algorithm enables agents to discover norms and to learn their values. Specifically, we (1) aggregate the sanctions and payoffs received by an agent into rewards; (2) map norms to IF-THEN rules to be manipulated by XCS; and (3) define crossover and mutation operations for norms to enable norm discovery.

XCS operates in two modes, *exploration* (take random actions to find new norms) and *exploitation* (apply learned rules and their weights to choose an action). We adopt the ϵ-greedy technique, choosing exploration with probability ϵ.

Each rule has associated parameters of *fitness* (worth of the rule in making accurate predictions), *reward prediction*, *prediction error* (of the reward), and *numerosity* (how many "copies" of the rule exist, indicating robustness against accidental deletion [Urbanowicz and Browne, 2017]).

Create Match Set. The *match set* is the set of rules that are activated in a given context. This means that the antecedents of the corresponding norms are true in the given context.

Cover Context. Covering ensures that rules with sufficiently many actions are available for a given context. Covering maintains diversity by adding new rules to the agent's ruleset, to avoid overfitting to the initial conditions. The new rules are generated by randomly selecting some subset of the context to be the antecedent of the rule. This ensures that the antecedent would be true in the given context. The consequent is randomly selected from available actions. Covering is essential at the beginning, since each agent has an empty ruleset, meaning its match set is empty.

Select Action. The expected value of each action aggregates the fitness-weighted reward predictions of rules supporting that action—to predict the expected reward of following each norm. Pick the available action with highest expected value.

Create Action Set. Matching rules that support a chosen action form the *action set*. We create this set by identifying which rules had suggested the selected action.

Update Rule Parameters. These updates follow Urbanowicz and Browne [2017]. Upon receiving a reward, the agent updates its parameters to update the value estimation of rules using the Widrow-Hoff update [Widrow and Hoff, 1960]. Only rules in the action set are updated as we don't know the impact of selecting any other action. Equation 1 updates the predicted reward. Here, p is the reward prediction, r is the reward received, and β is the rate of learning hyperparameter.

$$p \leftarrow p + \beta(r - p) \tag{1}$$

Equation 2 updates the prediction error, ε. Equation 3 estimates accuracy κ where ε_0 is the error threshold below which we assume a rule to be accurate. Here, v is controls the relationship between error and accuracy to increase the difference in fitness levels between two rules that are close in prediction error—to prefer a less error-prone rule during discovery. And, α is the scaling factor used to raise the least error-prone non-accurate classifier to be close to an accurate classifier.

$$\varepsilon \leftarrow \varepsilon + \beta(|r - p| - \varepsilon) \tag{2}$$

$$\kappa = \begin{cases} 1 & \text{if } \varepsilon < \varepsilon_0 \\ \alpha(\frac{\varepsilon}{\varepsilon_0})^{-v} & \text{otherwise} \end{cases} \tag{3}$$

We normalize accuracy to κ' using Equation 4, and update fitness F using Widrow-Hoff update:

$$\kappa' = \frac{\kappa}{\sum_{cl \in |A|} \kappa_{cl}} \tag{4}$$

$$F \leftarrow F + \beta(\kappa' - F) \quad (5)$$

Subsume Action Set Rules. Subsumption means replacing a more error-prone (**reward prediction**), less general rule with an existing less error-prone, more general rule. This process provides a generalization pressure to the algorithm. If the first rule below (R1) is more error-prone than the second (R2), it may be replaced by the second, thus increasing the latter's numerosity.

$$\text{IF urgent=}\top \ \wedge \text{callerRel = friend THEN ring} \quad \text{(R1)}$$
$$\text{IF urgent=}\top \text{ THEN ring} \quad \text{(R2)}$$

Discover Rules. We apply a genetic algorithm (GA) to generate new rules from current rules of high fitness. GA selects parents using *tournament selection* [Urbanowicz and Browne, 2017]. We use 30% of the action set size as the number of rules randomly selected to compete. The fittest two among them are chosen as parents (with replacement, so they can be the same rule). Two children are then generated using *crossover* and *mutation* operations, which we define for norms. The children are added to the population of rules maintained by the agent. To allow the rules to stabilize, we breed them only when the average experience (number of times a rule has been selected) of the rules in the current action set is above a threshold. We use single-point crossover, in which the values are randomly swapped for each contextual property present in either parent's antecedent.

In XCS, mutation is used to create a more general or more specific rule by randomly flipping bits in the parent encoding. For norms, we randomly add (using $\wedge$) or remove key-value pairs in the antecedent of the norm being mutated. For example, if the antecedent of a norm is {callerRel = friend $\wedge$ urgent = $\top$}, we may mutate it to {urgent = $\top$} by removing a pair or to {callerRel = friend $\wedge$ urgent = $\top$ $\wedge$ calleeLoc = home}, if the location in the current context is home.

Subsume Child Rules. Just after creation, a child rule is subsumed into its parent if the parent is a more generic version of the child and its error is less than a threshold.

Delete Rules. A hyperparameter defines the maximum number of rules a SIGA can keep. We apply Kovacs's [1999] deletion scheme 3, which prefers to delete unfit rules.

3.2 Norms as Explanations

An explanation is comprised of norms that support the action taken, i.e., the action set identified above. An agent evaluating the explanation finds norms it follows in the explanation plus the norms that have been violated. It adds these rules to the match set and then follows the same procedure as action selection by performing fitness-weighted aggregation of reward prediction. If the action selected matches the observed action, the sanction is avoided.

4 Simulation Scenario: RINGER

This scenario is based on our running example and is implemented using MASON [Luke *et al.*, 2005]. The simulation consists of a population of agents. There are five shared locations where agents can interact: homes (H), parties (P), meetings (M), a library (L) and an emergence room (ER). Some of these locations (H, P, and M) have an associated relationship circle. Each home has a family circle, each party has a friend circle, and each meeting has a colleague circle. People of the same circle share that relationship. Agents stay at one location for a random number of steps chosen from a Gaussian distribution with mean of 60 steps and standard deviation of 30, with the number of steps restricted to the range $[30, 90]$. Then they move to another location. They are more likely to enter a location that is associated with their own circles (75% probability) than a location with which they don't have an association (25% probability). For example, they are more likely to enter their own homes than a stranger's home.

At each timestep, each agent calls another agent with a probability chosen from a Gaussian distribution with mean of 5% and standard deviation of 1%. There is a 25% probability of calling a family member, 25% of calling a colleague, 25% of calling a friend, and 25% of calling a stranger.

All agents have goals based on their role (Table 1). The degree to which the agents are affected by the promotion or demotion of these goals determine the payoff that they receive. The payoff may differ based on location and relationship.

Table 1: Agent goals.

Role	Goal	Action
Caller	Reach callee either urgently or casually	Answer
Callee	To be reachable	Answer
	To not be disturbed	Ignore
	To not disturb others	Ignore
Neighbor	To not be disturbed	Ignore

Tables 2, 3, and 4 present the callee, caller, and neighbor payoffs, respectively. Neighbor payoffs and sanctions may be impacted by the explanation provided, depending on whether the explanation was accepted or not. Table 5 summarizes the expected payoff of each situation in this case.

Table 2: Callee payoff based on urgency and relationship.

Caller Relationship	Callee Action	Casual	Urgent
Family, Friend, Colleague	Answer	0.50	1.00
	Ignore	0.00	-0.50
Stranger	Answer	-1.50	0.50
	Ignore	1.50	-0.25

Table 3: Caller payoff based on urgency of the call.

Callee Action	Casual	Urgent
Answer	0.50	1.00
Ignore	-0.50	-1.00

4.1 Contextual Properties

The relevant context includes callee's location (home, party, meeting, library, and ER), relationship with caller (family,

Table 4: Neighbor payoff based on location of the call.

Callee's Action	ER	H	L	M	P
Answer	1.00	0.67	−1.00	−1.00	−0.33
Ignore	−1.00	−0.33	1.00	1.00	0.67

Table 5: Neighbor payoff based on evaluated explanations.

Callee Action	Neighbor Expects	ER	H	L	M	P
Answer	Answer	1.00	0.67	1.00	1.00	0.67
Answer	Ignore	−1.00	−0.33	−1.00	−1.00	−0.33
Ignore	Answer	−1.00	−0.33	−1.00	−1.00	−0.33
Ignore	Ignore	1.00	0.67	1.00	1.00	0.67

friend, colleague, stranger), and call urgency.

4.2 Types of Societies

Agents optimize their norms based on a weighted sum of payoffs received by each stakeholder. We define types of societies based on the generosity of their members in terms of the weight they place on the welfare (payoff) of their peers.

Selfish Members give weight only to their own payoff.
Pragmatic Members give equal weight to everyone's payoff.
Considerate Members give weight only to others' payoffs.
Mixed 25% selfish, 25% considerate, 50% pragmatic.

5 Experiments and Results

To address our research questions, we run simulations of pragmatic, selfish, considerate, and mixed agent societies using three kinds of agents: We evaluate three types of agents.

Fixed agents follow a fixed set of norms (Table 6). When norms conflict they choose a random action.
NSIGAs evolve a set of explicit norms following our mechanism. When they violate a norm, they accept the sanction and use that feedback to guide learning.
XSIGAs go beyond NSIGAs by explaining their actions and issuing sanctions based on explanations received.

Table 6: Norms followed by a fixed agent.

Location	Response
Emergency Room (ER)	Answer
Home (H)	Answer
Library (L)	Ignore
Meeting (M)	Ignore
Party (P)	Answer

Circle	Casual	Urgent
Colleague	Answer	Answer
Family	Answer	Answer
Friend	Answer	Answer
Stranger	Ignore	Answer

5.1 Evaluation Metrics and Hypotheses

We compute *Social Experience*, *Cohesion* and *Adoption*.

Social Experience measures the degree of goal satisfaction delivered by an agent [Ajmeri *et al.*, 2018]. We compute social experience as the weighted aggregate of payoffs received by all the stakeholders as the result of an agent's actions [Ajmeri *et al.*, 2018]. The weights depend on the nature of the agent (selfish, considerate, pragmatic) as defined in Section 4.2.

Cohesion measures the perception of norm compliance [Ajmeri *et al.*, 2018], and is defined as a ratio of agent's actions perceived as norm compliant by agents who are affected by each action divided by the total number of interactions.

Adoption measures the percentage of agents in a society who follow a particular norm. A norm is said to have emerged when a sufficiently high percentage of the population complies with the norm [Haynes *et al.*, 2017]. Recognizing literature [Shoham and Tennenholtz, 1997; Kittock, 1993; Delgado, 2002], we consider 90% adoption as the threshold for norm emergence.

We evaluate the following hypotheses: $\mathbf{H_1}$ and $\mathbf{H_2}$ relate to $\mathbf{RQ_G}$; $\mathbf{H_3}$ and $\mathbf{H_4}$ relate to $\mathbf{RQ_C}$; and $\mathbf{H_5}$ relates to our overall research objective of studying the impact of explanations on norm emergence. Each hypothesis compares the *XSIGA* approach with the other approaches. We omit the corresponding null hypotheses for brevity.

$\mathbf{H_1}$ XSIGAs give higher *social experience* than *Fixed* agents.
$\mathbf{H_2}$ XSIGAs give higher *social experience* than *NSIGAs*.
$\mathbf{H_3}$ XSIGAs give higher *cohesion* than *Fixed* agents.
$\mathbf{H_4}$ XSIGAs give higher *cohesion* than *NSIGAs*.
$\mathbf{H_5}$ XSIGAs give higher *adoption* of norms than *NSIGAs*.

We report results for each simulation run eight times for 10,000 timesteps. To evaluate these hypotheses, we conduct a paired t-test and measure the effect size as Cohen's d.

5.2 Experiment: Pragmatic Agent Society

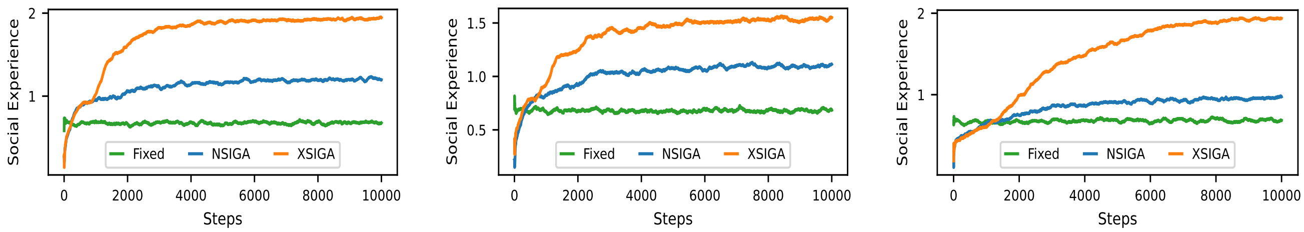
Table 7 summarizes the social experience, cohesion and adoption metrics yielded by the three agent types in a pragmatic society. Figure 1a compares the social experience plots for Fixed, NSIGAs, and XSIGAs agents in a pragmatic society. We find the social experience, cohesion and adoption yielded by XSIGAs to be better ($p < 0.01$; d> 0.8, indicating large effect) than the two baselines.

Table 7: Social experience and cohesion in pragmatic society.

Agent	Experience		Cohesion		Adoption	
	Mean	SD	Mean	SD	Mean	SD
Fixed	0.68	0.01	27.06%	0.10	–	–
NSIGA	1.21	0.01	55.65%	0.34	96.49%	0.10
XSIGA	1.94	0.01	88.81%	0.25	98.45%	0.22

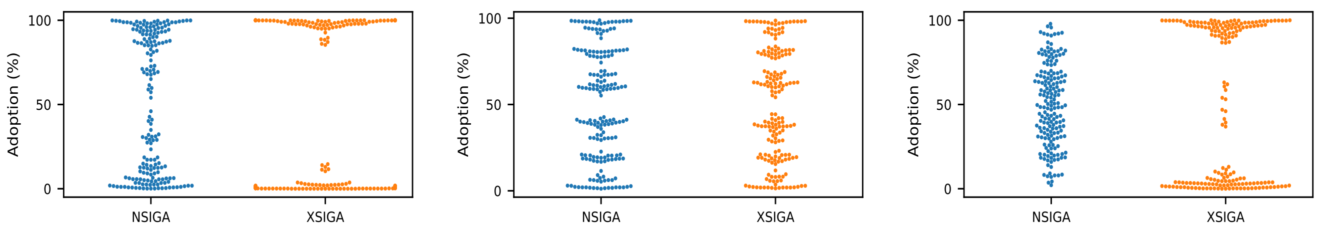
Figure 2a shows adoption of norms for different approaches in pragmatic society. We focus on the SIGA approaches because Fixed agents do not adopt new norms. Each dot is a norm. Providing explanations help in identifying useful norms and encourage their adoption, while discouraging the adoption of useless norms. As a result, it leads to a more extreme distribution of adoption—see Figure 2a.

Table 8 shows the norms that emerge using SIGAs. The norm emerged with XSIGA is to always ring. By ringing a call, the agent provides a better experience to the caller. The neighbor's experience depends on the acceptance or rejection



(a) Pragmatic Society. (b) Selfish Society. (c) Considerate Society.

Figure 1: Comparing social experience yielded by Fixed, NSIGAs, and XSIGAs in pragmatic, selfish, and considerate agent societies.



(a) Adoption of norms: Pragmatic Society. (b) Adoption of norms: Selfish Society. (c) Adoption of norms: Considerate Society.

Figure 2: Comparing adoption of norms by Fixed, NSIGAs, and XSIGAs in pragmatic, selfish, and considerate agent societies.

of the explanation. The callee experience can be negative in some cases like ringing a casual call by a stranger, but the pragmatic agent values payoffs of all agents and thus chooses to ring a call. NSIGAs get harsher penalties from their neighbors for violating norms as they cannot provide explanations. So they become more cautious about violations. As a result, the emerged norm is to ring an urgent call or call by a known person or call in an ER because these provide sufficient positive payoffs to overcome possible negative neighbor reactions. Whereas Figure 2a shows several norms with adoption more than 90%, Table 8 lists only one emerged norm for XSIGAs, *ring all calls*. This is because this norm is more general than all other emerged norms, such as *ring urgent calls*.

Table 8: Norms in Pragmatic Society, XSIGAs and NSIGAs.

Antecedent	**Consequent**	**Adoption**
	XSIGAs	
true	ring	91.2%
	NSIGAs	
urgent = $\top$	ring	97.4%
callerRel = colleague	ring	93.1%
callerRel = family	ring	92.7%
calleeLoc = home	ring	92.4%
callerRel = friend	ring	92.2%
calleeLoc = ER	ring	92.2%

5.3 Experiment: Selfish Agent Society

Table 9 summarizes the social experience, cohesion and adoption metrics yielded by the three agent types in a selfish society. Figure 1b compares the social experience plots for Fixed, NSIGAs, and XSIGAs agents in a selfish society. We find the social experience and cohesion yielded by XSIGAs to be better ($p < 0.01$; d$>$ 0.8, indicating large effect) than the two baselines, and thus reject the null hypotheses corresponding to H_1–H_4. For adoption we find that the difference in mean values is not statistically significant, thus we fail to reject the null hypothesis corresponding to H_5.

Table 9: Social experience and cohesion in selfish society.

Agent	**Experience**		**Cohesion**		**Adoption**	
	Mean	SD	Mean	SD	Mean	SD
Fixed	0.68	0.02	27.09%	0.13	–	–
NSIGA	1.10	0.01	49.20%	0.13	96.07%	0.22
XSIGA	1.55	0.01	68.46%	0.23	95.94%	0.31

Figure 2b shows adoption of norms for different approaches in a selfish society. Providing explanations has a lower impact on emergence in a selfish society than others. This is because an explanation is meant to explain the agent's actions to the other agents to get a positive response. But selfish agents don't give weight to anyone's payoff other than their own and thus do not give value to responses from other agents. As a result, they only learn norms that benefit themselves without caring about evaluation of explanation. They still provide and evaluate explanations, but they don't let it influence the norm they learn. This is the reason that the mean adoption among emerged norms is similar for XSIGAs and NSIGAs. Providing an explanation is better in terms of social experience and cohesion because neighbors are also selfish agents who can accept an explanation based on a norm learnt due to selfish tendencies. This acceptance of explanation lead to better social experience and cohesion, even if it doesn't impact the exact norms that emerge.

Table 10 shows norms that have emerged using SIGAs. The norms emerged for XSIGAs and NSIGAs are similar, in line with our expectation that norms emerging in a selfish society won't be impacted by providing explanations. The emerged norm is to pick up an urgent call and to always ignore a casual call from a stranger. This is because a selfish agent does not value the payoff of neighbors or callers. It ignores a casual call from a stranger even in a nonrestrictive location like ER where the neighbors expect it to ring a call.

Table 10: Norms in Selfish Society, XSIGAs and NSIGAs.

Antecedent	**Consequent**	**Adoption**
XSIGAs		
urgent = $\top$	ring	91.4%
urgent = $\perp \wedge$ callerRel = stranger	ignore	90.2%
NSIGAs		
urgent = $\top$	ring	91.4%
urgent = $\perp \wedge$ callerRel = stranger	ignore	90.2%

5.4 Experiment: Considerate Agent Society

Table 11 summarizes the social experience, cohesion and adoption metrics yielded by the three agent types in a considerate society.

Figure 1c compares the social experience plots for Fixed, NSIGAs, and XSIGAs agents in a considerate society. We find the social experience, cohesion and adoption yielded by XSIGAs to be better ($p < 0.01$; d> 0.8, indicating large effect) than the two baselines, and thus reject the null hypotheses corresponding to H_1–H_5.

Table 11: Social experience, cohesion: considerate society.

Agent	**Experience**		**Cohesion**		**Adoption**	
	Mean	SD	Mean	SD	Mean	SD
Fixed	0.69	0.01	27.11%	0.14	–	–
NSIGA	0.97	0.02	69.72%	0.24	93.70%	0.23
XSIGA	1.93	0.01	77.48%	0.63	97.18%	0.30

Figure 2c shows adoption of norms for different approaches in a considerate society. As in a pragmatic society, providing explanations had a polarizing effect on adoption. This helps in emergence of norms by increasing adoption of the emerged norms.

Table 12 shows explicit norms that have emerged using SIGAs. For XSIGAs, the effective norm is to ring in all cases due to similar reasons as the pragmatic agent. We have shown that even within the norm, a more specialized version like ringing an urgent call has higher adoption than ringing a casual call. For NSIGAs, the agent needs to be more careful with the neighbor payoff, as for pragmatic agents. As a result, the most adopted norms are based on location and urgency.

Table 12: Norms in Considerate Society, XSIGAs and NSIGAs.

Antecedent	**Consequent**	**Adoption**
XSIGAs		
urgent = $\top$	ring	97.4%
urgent = $\perp$	ring	92.2%
NSIGAs		
urgent = $\top \wedge$ calleeLoc = home	ring	92.0%
urgent = $\top \wedge$ calleeLoc = ER	ring	92.3%
urgent = $\perp \wedge$ callerRel = stranger	ignore	90.2%

6 Discussion

We find that societies composed of XSIGAs have better social experience and cohesion than the baselines and that providing and evaluating explanations leads to better adoption of emerged norms, except for a selfish society.

This work exposes some interesting extensions. One, generate explanations that preserve privacy. The tradeoff between privacy and specificity would be interesting. Two, an ontology of terms could help learn norms with complex boundaries. Three, SIGAs can be enhanced to incorporate value preferences, ethics and fairness in explicit norm emergence [Serramia *et al.*, 2018; Santos *et al.*, 2019].

Mosca and Such [2021] generate explanations in multiuser privacy scenarios for evaluation by a human. In contrast, our explanations are communicated between agents for norm emergence. Hind *et al.* [2019] apply machine learning to jointly predict actions and explanations. In contrast, our explanations are the norms that explain an action.

Morales *et al.* [2014] study centralized norm emergence where conflict scenarios are recognized and norms adapted to handle the conflicts. But, here, agents themselves create the norms. Morales *et al.* [2018] synthesize norms using an offline, centralized mechanism to evolve norms aligned with goals, whereas here norms evolve in an online, decentralized manner based on sanctions. Mashayekhi's [2016] decentralized norm emergence framework is driven by conflict detection with norms created to avoid conflicts. But, here, SIGAs are driven by sanctions and sharing explanations.

Dell'Anna *et al.* [2020] uses Bayesian Networks to revise sanctions associated with enforced norms. In contrast, we revise the norms themselves while the sanctions stay the same. Hao *et al.* [2018] propose heuristic collective learning frameworks to learn norms as best responses to all states whereas we apply genetic exploration to evolve the antecedents used in the norms, instead of learning for all states.

Ajmeri *et al.* [2018] provide an implicit norm system that learns actions to be taken in different contexts, whereas our work is an explicit norm system that explicitly learns and reasons about norms. They share not explanations but the entire context in which the decision was made to violate the norm. This context is evaluated by other agents to decide if they would have done the same action as a basis for sanctioning. In contrast, we share explicit norms that influence a decision.

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