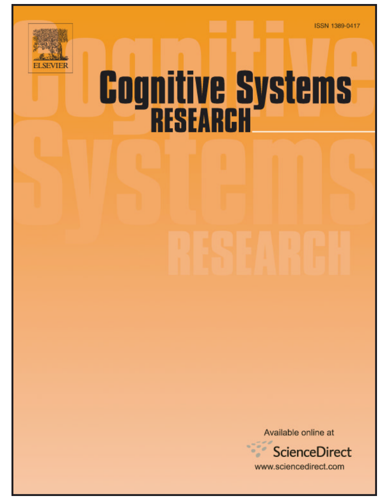

Social Learning in Repeated Cooperation Games in Uncertain Environments

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Abstract

Cooperation and social learning are fundamental mechanisms that maintain social organisation among animals and humans. Social institutions can be conceptualised abstractly as cooperation games with social learning. In some cases potential cooperation partners may be easily identifiable, while in other cases this is difficult. Real world institutions always operate in uncertain environments. Here we use agent-based simulation to explore the interaction between social learning, cooperation and environmental uncertainty with and without easy to identify cooperation partners. Our agents use a communication language to indicate their cooperation intentions. We discuss the measurement of communication or language complexity metrics, which may be used as correlates of the level of cooperation. The results show that more uncertainty induces more cooperation and that social learning increases the level of cooperation. We show that the positive impact of social learning is bigger in low uncertainty environments than in high uncertainty environments and also in cases where identification of potential cooperation partners is harder. The results suggest that environmental uncertainty, social learning and easy identification of cooperation partners may play alternating roles in the promotion of cooperation in social institutions and the expansion and development of these institutions.

Keywords:

agent-based modelling, cooperation, evolutionary simulation, institution modelling, social learning, uncertainty

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1. Introduction

Cooperation between individual humans provides the foundation for organisation and functioning of societies (Smaldino, 2018; Wu et al, 2015; Pletzer et al, 2018). Cooperation plays also a similar key role in animal societies as well (Moehlman, 1986; Moscovice et al, 2017) and is present as a special form of interaction between individuals even in communities of non-social animals and plants, which do not constitute complex societies (Dugatkin, 1997; Callaway et al, 2002; DeBono et al, 2002). The roots of cooperative behaviour, when joint benefits are preferred to potentially larger individual benefits, are likely to go deep into the biology of living beings. At the same time cooperative behaviour is at odds with the selfish interests of individual organisms. There are a few key theories that aim to explain the emergence of cooperation among selfish individuals, e.g. kin selection, reciprocal altruism, image scoring (Axelrod, 1997; Rand and Nowak, 2013; Sigmund et al, 2010).

Cooperation games, such as the Prisoner's Dilemma (PD), emerged in the context of formalised study of human social decision making behaviour (Axelrod, 1997). These games are typically played by two partners, who chose their individual action and then the game delivers a pay-off to both partners, depending on a pay-off matrix associated with the combinations of individual actions. Most commonly the players can choose between two individual actions that can be conceptualised as 'cooperate' and 'defect'. Repeated cooperation games provide a conceptual model for social behaviour and in particular for the study of mechanisms for the emergence of cooperation in social context (Dugatkin, 1997; Rand and Nowak, 2013). Repeated games allow participants to use their past experience to form their decisions and also for the selection of best game playing strategies (i.e. rules and patterns of game decision selection) across many rounds of repeated games or even across many generations of players.

Social learning is the process by which individuals copy in some sense and to some extent the behaviour of other individuals within their observational range (Bandura, 1971; Boyd and Richerson, 2009; Flinn, 1997; Heyes, 1994). Social learning in particular relates to copying behaviours that are expected to bring benefits to the individual who generates these behaviours. Social learning is expected to play an important role in social organisation by facilitating the spreading of behaviours beneficial for effective social organisation (Boyd and Richerson, 2009; Pahl-Wostl et al, 2007; Sigmund et al, 2011; Wenger, 2000).

Given that both repeated cooperation games and social learning are assumed to capture important aspects of how social organisation emerges in societies, it is important to understand how these two mechanisms interact. To what extent does social learning support the emergence of high level of cooperation, and to what extent does it reduce the variability and adaptation potential of the community? Is there any particular context where social learning is more or less effective in supporting the emergence of high level of cooperation?

Environmental uncertainty captures variability of the social and natural context of social interactions (Andras et al, 2003; Andras et al, 2007; Krams et al, 2010; Spinks et al, 2000; Rand et al, 2013; Potts and Faith, 2015). Environmental uncertainty can be integrated into the game playing through altering the pay-off values, while maintaining the regularities that define the cooperation game (e.g. the inequalities between the various pay-off values corresponding to different decision combinations). This allows the study of the impact of environmental uncertainty on game playing and on strategy selection in repeated games. A further factor influencing the level of cooperation is the ease of identification of potential cooperation partners (Andras , 2016; Mitteldorf and Wilson, 2000). In general, easier identification of prospective cooperators is likely to increase the level of cooperation. Adding in social learning among players allows to investigate the interplay between the environmental uncertainty, social learning and identifiability of cooperators in the setting and driving the level of cooperation.

Here we present results from an agent-based simulation study, where the agents play a PD game in the context of an uncertain environment. We investigate the effect of adding social learning into the agent worlds in terms of the impact of this on the level of cooperation that emerges and is sustained in the simulated worlds. Our agents use a probabilistic communication language to reach their decisions in the uncertain PD games that they play. The offspring of the agents may cluster together or may be spread out, representing the easy and difficult identification of potential cooperation partners. In addition to the level of cooperation we also measure correlates of these, such as the length of agent communications and variability of the agent's communication language. Our analysis shows that social learning in all contexts helps to raise significantly the level of cooperation among the agents. At the same time it also reduces the variability of the agent's language and the length of agent communications, increasing the conformity in the agent communities. The results are interpreted in the context of their relevance for the evolution of social institutions.

The rest of the paper is structured as follows. First we review briefly the relevant background research. Then we discuss social learning in the context of cooperation games. Next we describe the methods that we use to measure correlates of cooperation. Next we present the simulation environment that we use. This is followed by the presentation of the results and the discussion on the margin of these. Finally the paper is closed by the conclusions section.

2. Background

Cooperation theory aims to explain the puzzle of emergence of cooperation among selfish individuals (Axelrod, 1997). One approach explains cooperation on the basis of genetic relatedness of individuals, i.e. cooperation supports the combined fitness of the genes that determine the individuals (Rand and Nowak, 2013). An alternative approach suggests that cooperation is rooted in reciprocal helping, i.e. if one individual provides help to another it can expect help from the other one in a different situation (Rand and Nowak, 2013). The indirect reciprocity approach assumes that individuals observe other individuals and help those who are seen to help others (Santos et al, 2018). There are other theories as well, e.g. explanations based on joint investment of time and effort (Roberts and Sherratt, 1998), spatial constraints (Mitteldorf and Wilson, 2000; Rand and Nowak, 2013), or group selection (Boyd and Richerson, 2009). However, in general, none of these theories is sufficient to explain all observed cases of cooperation among humans, animals, plants and microbes.

Social learning, i.e. the learning of behaviour from other individuals of the same species, has been described in one or another form in the context of many animal communities (Heyes, 1994). In general, in social learning individuals copy the behaviour of another individual (e.g. the oldest or the strongest or the most successful in some particular sense) or the most frequent behaviour across many other individuals (Bandura, 1971; Boyd and Richerson, 2009; Csibra and Gergely, 2006; Flinn, 1997; Mesoudi et al, 2014). The mechanism of social learning in general is the observation of the behaviour of other individuals and the copying or imitation of this behaviour (Csibra and Gergely, 2006; Heyes, 1994; Rendell et al, 2010). The imitation is usually not perfect, but rather approximate and partial, giving rise to variations in the imitated behaviour (Csibra and Gergely, 2006; Mesoudi et al, 2014). Social learning appears to play a critical role in the emergence and maintenance of social norms and social institutions (Pahl-Wostl et al, 2007; Sigmund et al, 2011; Wenger, 2000).

It has been suggested that social learning contributes importantly to the emergence of cooperation (Boyd and Richerson, 2009; Chudek et al, 2013; Rendell et al, 2010; Smaldino, 2018). In a sense social institutions can be seen as the frameworks of cooperation games and social institutions emerge and are sustained through social learning processes. The scale and speed of emergence and spreading of cooperative behaviour among humans in a range of social settings can be explained by considering fast social learning that can act much more rapidly that biological selection of best behavioural patterns (Boyd and Richerson, 2009). Thus social learning appears to be a requirement for the current scale of widespread cooperation among humans in the context of many social institutions. However, there are also studies that question the suggested role of social learning in the evolution of human cooperation (Heyes, 2013).

The evolution of cooperation and the combination of this with social learning and cultural evolution has been the subject of intense investigation in the context of social physics research (Szabo and Toke, 1998; Szabo and Fath, 2007; Castellano et al, 2009; Perc et al, 2013; Perc et al, 2017). This research considers both the case of well-mixed populations, where all individuals may interact with any other individual, and the case of structured populations in which individuals can interact only according to a neighbourhood network (Szabo and Fath, 2007; Nowak et al, 2010). This line of research uses the conceptual framework and analytical tools of statistical physics to explore the large-scale dynamics of decision strategies in communities of agents. In models that incorporate social learning or cultural evolution the decision strategies may change according to a usually probabilistic rule (e.g. adopting the neighbour's decision strategy with some probability if that is more successful according to some criteria – for example gaining resources following repeated playing of an abstract game) (Castellano et al, 2009; Perc et al, 2013). However, the models of social physics rely typically on simple agents characterised fully by their decision strategy and possibly position within the neighbourhood network, which facilitates the application statistical physics concepts and tools, but does not allow implementation of inner mechanisms of individual agents that may influence and change their individual decision making. While the power of the social physics approach is very much appreciated, here in this paper the implementation of such inner mechanisms of agents is considered important (see Section 5).

Environmental uncertainty in general refers to the variability of some aspects of the environment that are important for the survival or successful life of the individuals (Andras et al, 2003; Mehta et al, 1999). For example, environmental uncertainty may refer to the risk of predation or the variability of the available food or water resources or the variability in the availability of sufficiently protective shelter (Krams et al, 2010; Spinks et al, 2000; Rand et al, 2013). Often environmental uncertainty is triggered by environmental adversity, i.e. the general lack of supporting resources in the environment (Andras et al, 2007). For example, an arid or cold environment increases the uncertainty of the environment by rendering moderately useful resources insufficient. Environmental uncertainty appears to play a major role in the evolution of many species (Callaway et al, 2002; DeBono et al, 2002; Popat et al, 2015) and in particular in the social evolution of humans (Pahl-Wostl et al, 2007; Mehta et al, 1999; Dequech, 2004).

There are a number of examples of animals, plants and microbes (Krams et al, 2010; Spinks et al, 2000; Potts and Faith, 2015; Callaway et al, 2002; DeBono et al, 2002; Popat et al, 2015) which show that more adverse or explicitly more uncertain environments are characterised by higher levels of cooperation (e.g. increased group size, more time spent on joint activity). It is assumed that the acceptable level of experienced environmental uncertainty is in a relatively narrow range for a community of individuals characterised by a set of social institutions. Cooperation through social institutions reduces the experienced uncertainty. More cooperation is needed for this in more uncertain environments. Thus uncertainty of the environment can drive higher the level of cooperation in a community of individuals as the experienced uncertainty is reduced through cooperation (Andras et al, 2003; Andras et al, 2007; Andras, 2008).

Collecting experimental evidence about cooperative behaviour and social learning is complicated and expensive in any natural setting. An alternative approach is to use agent-based models and simulations to explore the impact of certain features of individual behaviour of the environment on the processes of cooperation and social learning (Andras et al, 2003; Axelrod, 1997; Nakahashi et al, 2012). Many simulation experiments have been conducted to explore mechanisms of social learning (Nakahashi et al, 2012; Molleman et al, 2013), cooperation (Pepper, 2007), and the role of social learning in the emergence and maintenance of cooperation (Seltzer and Smirnov, 2015). For example, it has been shown that social learning among distant individuals increases the level of cooperation, while conformism may reduce the level of cooperation (Molleman et al, 2013; Burton-Chellew et al, 2015). Several agent-based simulation studies have shown the positive impact of increased environmental uncertainty on the sustained level of cooperation (Andras et al, 2003; Andras et al, 2007; Andras, 2008), while many others looked at the various proposed mechanisms responsible for the emergence of cooperation (Axelrod, 1997; Bear and Rand, 2016; Bristow et al, 2014). Simulation studies also confirm that the clustering of agents ready for cooperation increases the level of cooperation in the agent community (Andras, 2016; Mitteldorf and Wilson, 2000).

3. Social learning in cooperation games

Practical cases show that social learning matters for maintaining cooperation practices among selfish individuals. For example, in the case of punishment of defectors in the context of managing and using public goods, copying the compliance behaviour avoids the punishment of individuals and at the same time increases the likelihood of cooperative behaviour and decreases the likelihood of defection behaviour (Sigmund et al, 2010). Social learning has been considered by many management researchers as a mechanism to instil behavioural patterns and rules within organisations, which in turn help maintain cooperative behaviours and support cooperative decision making within the organisation (Pahl-Wostl et al, 2007; Wenger, 2000). Social learning works in similar ways in animal communities as well. For example, in some cases when wolves fight the loser offers his throat to the winner, which in turn does not kill him, but lets the loser leave. Copying this behaviour helps the community of wolves to maintain sufficiently high number of individuals, while also allowing them to establish the social hierarchy within the community. Having sufficiently many individuals increases the likelihood of success of cooperative hunting of the wolf pack.

Cooperation games in general can be seen as an abstract conceptualisation of social institutions, where social institutions are seen as systematic sets of behavioural rules and patterns that channel social decision making processes (Goist and Kern, 2018; Kube et al, 2014). In an abstract sense the social institutions are about generating a decision with social impact and participants in the institutions follow some rules to reach their own contribution to the decision making process. In the simplest form, there are two participants who pick their own decision options and the social decision is computed using decision table that indicates the social outcomes of the combinations of the individual decision options. For example, individuals may play a resource game, where individual contributions to the resource generating effort lead to the combined resource outcome, e.g. cooperative hunting or foraging (Lönnstedt et al, 2014). Another example is the defence game, where individuals contribute to the defence effort, e.g. vigilant behaviour aimed to detect predators (Townsend et al, 2011) or offering alternative target for predators (Rieucau et al, 2015; Seghers, 1974), and gain collectively improved chance of survival. A further game is the fighting game, where individuals fight for position in the social hierarchy mainly by posturing and vocalisations and possibly by limited amount of actual physical fight, however achieving the final outcome usually without significant wounds or physical damage (Schilder et al, 2014; van der Borg et al , 2015). Human social institution games are typically more complex and involve multiple individuals however, conceptually they follow similar patterns of decision making and outcome generation. Institutional decision making processes with many components can be conceptualised as simultaneously played cooperation games, characterised by distinct communication processes about decision contributions and specific decision tables for the generation of decision outcomes. A further factor that influences the playing of institutional cooperation games is the clustering or lack of clustering of individuals with higher willingness to cooperate (Andras, 2016; Mitteldorf and Wilson, 2000). Here the term clustering includes the possibility of easy identification of co-operators, e.g. rank or group membership identifiers. Naturally, it is expected that cooperation levels are higher if likely co-operators can be identified (Andras, 2016).

Social institutions rely to considerable extent on social learning to maintain themselves (Mesoudi et al, 2014; Sigmund et al, 2011; Wenger, 2000). Individuals who get involved in these institutions get their initiation though copying and following behavioural patterns of other participants of the institutions. For example, consider initiation into religious institutions through learning and copying appropriate behaviours, e.g. singing, dancing, participation in processions, chanting, saying or shouting specific sequences of words or vocalisations, producing particular postural and behavioural patterns, etc. Social institutions provide also channels for social learning, by directing the copying behaviour along the components of the institution and facilitating or prizing certain forms of social learning. Social learning may be reinforced through provision of punishment or reward (Sigmund et al, 2011), e.g. by leaving the individual to the last round of feeding or letting them into one of the first rounds depending on their contribution to the hunting. Social learning may rely on observing others and gradually producing copied behaviour that increasingly matches the desired behaviour (Csibra and Gergely, 2006), e.g. learning to read, write or work with numbers from a teacher. In general social learning may rely on close to perfect copying of some behavioural patterns or on partial copying of most behavioural patterns and the gradual expansion of the range of the copied behavioural patterns or of the extent of precision of copying of the behavioural patterns. The copied behaviours may be those of the individuals who are most successful in some appropriate sense (e.g. get the most and best food, most successful in fighting or mating) or the behaviours that are most frequently produced among other individuals (e.g. singing in the church).

Given that institutions are conceptualised as cooperation games and institutions rely on social learning, it is natural that social learning influences cooperation, as we already indicated through the examples noted above. Copying of behaviour of others in the context of formal cooperation games equates to the copying of the strategy rules, as much as these can be determined from the observed behaviour of individuals. If the strategy is implemented through a set of communication rules (e.g. communication of intentions, similar to posturing and vocalisations in fighting games) then copying of the behaviour can be implemented by copying of such communication rules. As noted above, copying may happen through exact copying of some communication rules or partial copying of most (or all) communication rules. Considering the identification of likely partners for cooperation, it is expected that if this identification is easy, e.g. signalling of group membership, social learning might have additional mechanisms for members of different cooperation-willingness groups. This is likely to increase the impact of social learning in such settings.

Uncertainty of outcomes or impact of institutional decision making can have significant influence on the functioning of the institutions (Dequech, 2004; Mehta et al, 1999; Rosendorff and Milner, 2001). For example, the outcomes of management decisions related to common goods may vary depending on the variable natural conditions (e.g. impact of cold or hot weather, flooding, wildfires, etc.). In general institutions are seen as mechanisms to reduce uncertainty induced by the environment (Mehta et al, 1999; Rosendorff and Milner, 2001) (e.g. consider simple forms of insurance or credit union associations). This effect is natural, considering institutions conceptualised as cooperation games, since cooperation in repeated cooperation games reduces the uncertainty experienced by the individuals participating in the games (Andras, 2006). Social learning induced by participation in institutions must impact on the playing of the cooperation games in uncertain environments. While social learning in principle is likely to increase the level of cooperation, assuming that those who cooperate frequently are also the most successful individuals, at the same time social learning may lead to excessive conformity as well, which prevents the emergence of alternative solutions of decisional problems that may lead to improved impact outcomes.

In general it is expected that the presence of social learning in repeated cooperation games leads to increased level of cooperation. An example of this can be considered the use of communal, institutional, management of common goods (e.g. highland meadows) instead of simple one-to-one agreements between joint users. The institutional approach induces social learning and more stable high level of cooperation than the alternative solution of multiple one-to-one agreements, leading to better and more sustainable management of the common goods. However, in general it is difficult to find good natural set-ups where the presence or absence of institutional organisation is given and it is also easy to measure the level of cooperation. In principle, international comparison of institutional environments with more and less cheating (e.g. indicated by level of corruption) is possible, however, sufficiently detailed measurement of social learning and cooperation practices is likely to be difficult. An alternative way to investigate the relationship between social learning and cooperative behaviour is through computational simulations. While these are naturally limited by the simplifying assumptions adopted in such simulations, they may offer insight in key aspects of this relationship and possibly allow the more valid interpretation of available data about real world scenarios and systems.

4. Measuring cooperation and its correlates

Measuring directly the level of cooperation in real world situations might be difficult. In the context of animal communities this may require detailed and long-term observation of many animals such that individual animals can be clearly identified and their interactions can be clearly classified as cooperation or non-cooperation. In the case of humans such observations in real world situations are even more complicated due to ethical considerations. One option to measure directly cooperation is to set up cooperation experiments with human participants (Sigmund et al, 2011), however such experiments are limited by the experimental settings and do not necessarily match real world situations. At the same time, the results of such experiments may be influenced by unintended factors brought in by the human participants, which are not or cannot be controlled by the experimenters (e.g. cultural background, language, emotional state of the participants).

As we noted in the previous section cooperation among individuals reduces the experienced uncertainty of individuals in the context of cooperation in uncertain environments (Andras, 2006). This is because cooperation allows the participants to share their outcome uncertainty, which effectively reduces the individually experience uncertainty. In the real world there are many sources of environmental uncertainty. These include unequal distribution of food resources, predation risk, availability of tools and environmental features that can improve winning chances in fights, unpredictable environmental events (e.g. floods, fires, earthquakes), unpredictable responses of humans to management decisions, and so on. In principle, measuring the experienced uncertainty of individuals could offer an indirect way of measuring the level of cooperation among the individuals.

Another way to reduce experienced uncertainty is to reduce the uncertainty induced by communications involved in the generation of decisions about cooperation and defection (Andras, 2008). The communication actions (behavioural, vocal or verbal) generated by individuals can be measured through an appropriate sample of these (i.e. complete and finely detailed measurement is not necessarily required) and the uncertainty induced or represented by these communications can be measured. There are two generic ways of measuring communication uncertainty, both are inspired by the Kolmogorov complexity (Andras, 2008). One approach is to measure the length of communications that lead to the cooperation / defection decision. According to this approach longer communications are more complex and more uncertain, so reduction of communication uncertainty is represented by a reduction of the average length of communications required for reaching these decisions. For example, let us assume that measured communication sequences (e.g. sequences of words) are as follows

$$C_i : m_i^1, m_i^2, \dots, m_i^{k_i}, i = 1, \dots, n;\ m_i^j \in A \tag{1}$$

where A is a set of communication symbols (e.g. words), m_i^j are communication symbols and C_i are the communications. Then the length based communication complexity metric for these communications is

$$\gamma = \frac{1}{n} \cdot \sum_{i=1}^{n} k_i \tag{2}$$

The other approach is to look at probability distributions of consecutive communication actions and calculate the variance (or standard deviation) of these distributions. Larger standard deviations mean more variability in the possible continuation communication actions and consequently imply higher uncertainty produced by the decision making communications. Following this approach reduction of uncertainty is represented by reduction of the standard deviations (e.g. the average of these standard deviations) of the communication continuation distributions. For example, considering a large corpus of communications of the form in equation (1), with $A = \{\omega_1, \omega_2, \dots, \omega_q\}$ being the set of symbols and each communication labelled by the individual who generated it, we measure the continuation probabilities of communication symbols for each individual as $P(\omega_i, \omega_j; w)$, where $w \in I$ are the labels of individuals (I being the set of the individuals) and (ω_i, ω_j) any pair of symbols. Then we measure the variance based communication complexity as follows:

$$\bar{p}_{i,j} = \frac{1}{|I|} \cdot \sum_{w \in I} P(\omega_i, \omega_j; w) \tag{3}$$

$$\theta_{i,j} = \frac{1}{|I| - 1} \cdot \sum_{w \in I} \left(P(\omega_i, \omega_j; w) - \bar{p}_{i,j} \right)^2 \tag{4}$$

$$\bar{\theta} = \frac{1}{q^2} \cdot \sum_{i=1}^{q} \sum_{j=1}^{q} \theta_{i,j} \tag{5}$$

where $\bar{\theta}$ is the communication complexity metric. Both measures of language induced uncertainty can be calculated using a sufficiently large sample of the communications used by the individuals, without requiring an exhaustive measurement of all communications of all individuals.

In general it is expected that reduction of experienced uncertainty happens through both cooperation and through reduction of communication induced uncertainty. Thus measuring the language induced uncertainty provides correlates of cooperation in the considered community of individuals. Given that measuring these correlates may be easier than measuring the level of cooperation itself or measuring the actual level of experienced uncertainty, they provide ways of measuring indirectly the level of cooperation. However, the actual relationship between these correlates and the effective level of cooperation may be less simple, and more exploration of this relationship may be needed for correct interpretation of correlate measurements for the purpose of estimating the level of cooperation.

In the presence of social learning which leads to copying of communication behaviours it is expected that language uncertainty correlates of cooperation will be affected. In particular, it is expected that the variability of language rules gets reduced and also possibly the length of communications gets reduced as well as individuals copy the behaviour of others. This may interfere with the relationship between the level of cooperation and the measures of the communication-based correlates, so further investigation is needed to establish the extent and direction of this interference.

Given that measuring cooperation and its communication-based correlates is complicated in real world settings an alternative way to address the evaluation of the relationships between these measures is to perform simulation experiments. Of course, such simulation experiments have their own limitations, however they can be controlled in detail and by implementing communications and cooperative games in sufficient detail they allow us to measure the level of cooperation and the communication-based correlates to establish their relationships.

5. The simulation environment

Our simulated world is inhabited by agents that own resources, communicate with each other and move around using random Brownian motion. The world of the agents is a 1000 x 1000 size square, with opposite edges glued together. The agents make random moves in the range of [-5,5]. The agent communications are about the intentions of the agents in the context of playing a Prisoner's Dilemma game. The agents play the game repeatedly with multiple partners. The game playing leads to generation of resources and the agents use resources to survive. The resource game that the agents play has uncertainty embedded in it, as the amount of generated resources varies.

The communication language of the agents is defined using a probabilistic automaton. The language rules determine the production of communication symbols, depending on the communication symbols that were produced previously by the interacting agents. Thus the language rules have the following form:

$$R: \left(m_{own}^{R}, m_{other}^{R}\right) \rightarrow_{p_1} m_{new}^{1}; \rightarrow_{p_2} m_{new}^{2}; \dots; \rightarrow_{p_{k_R}} m_{new}^{k_R} \quad (6)$$

where m_{own}^{R} and m_{other}^{R} are the last symbol produced by the agent and its communication partner, m_{new}^{i} are the new symbols that the agent may produce using the rule, p_i is the probability of production of this symbol following this rule and k_R is the number of new symbols that may be produced using the rule R. We note that $\sum_{i=1}^{k_R} p_i = 1$. A simplified representation of the rule, without the specification of the probabilities, but including the list of possible produced symbols is

$$R: \left(m_{own}^{R}, m_{other}^{R}\right) \rightarrow \{m_{new}^{1}, \dots, m_{new}^{k_R}\} \quad (7)$$

In our simulation the symbols used by the agents are: {0, s, y, n, i, t, h} with the following meaning: 0 – wait, s – start effective communication, y – engage in decision making, n – stop communication and return to waiting state, i – continue communication, t – take defection decision, h – take cooperation decision. The language rules are as follows: $(0,0) \rightarrow \{0, s\}$; $(0, s) \rightarrow \{0, s\}$; $(s, 0) \rightarrow \{0, s\}$; $(s, s) \rightarrow \{y, n, i\}$; $(s, s) \rightarrow \{y, n, i\}$; $(s, i) \rightarrow \{y, n, i\}$; $(i, s) \rightarrow \{y, n, i\}$; $(s, y) \rightarrow \{y, n, i\}$; $(y, s) \rightarrow \{y, n, i\}$; $(i, i) \rightarrow \{y, n, i\}$; $(i, y) \rightarrow \{y, n, i\}$; $(y, i) \rightarrow \{y, n, i\}$; $(s, n) \rightarrow \{0\}$; $(n, s) \rightarrow \{0\}$; $(i, n) \rightarrow \{0\}$; $(n, i) \rightarrow \{0\}$; $(y, n) \rightarrow \{0\}$; $(n, y) \rightarrow \{0\}$; $(n, n) \rightarrow \{0\}$; $(0, n) \rightarrow \{0\}$; $(n, 0) \rightarrow \{0\}$; $(y, y) \rightarrow \{h, t\}$; $(h, y) \rightarrow \{h\}$; $(t, y) \rightarrow \{t\}$; $(y, h) \rightarrow \{h, t\}$; $(y, t) \rightarrow \{h, t\}$. The joint cooperation decision is achieved if both interacting agents decide to communicate h. One agent defects and takes advantage of the other, if one of the agents communicates t, while the other communicates h. Both agents defect and neither of them gains advantage at the cost of the other, if both agents communicate t. If both agents do not reach the communication of the symbol s within T_{start} communication steps ($T_{start} = 10$) the communication ends and neither agents cooperate (i.e. equivalent of the final communication of t by both agents). If both agents reached the communication of the symbol s within T_{start} communication steps, but they cannot reach the communication of symbol combinations (t, t), (t, h), (h, t) or (h, h) within T_{decide} communication steps ($T_{decide} = 50$), again the communication stops in the equivalent state of communicating (t, t) by the two agents. The communication symbols are arranged in a positivity order: t, n, 0, s, i, y, h. The language rules obey an intention consistency constraint in the sense that if a symbol m can be produced immediately following the production of the symbol m' with probability p' and also immediately following of the symbol m'' with probability p'', and m is more positive than m' and m' is more positive than m'', then $p' \geq p''$. In other words, the likelihood of communication of increasingly positive intentions does not drop as more positive intentions are communicated. All agents share the same set of language rules, but each agent has its own setting of the probabilities for each language rule such that these probabilities satisfy the intention consistency constraint.

In each time turn of the world the agents try to find a communication partner. They choose their partner from agents which neighbour them in the spatial world of the agents. The agents consider the closest $N_{neighbour}$ agents ($N_{neighbour} = 10$) as potential partners. If all potential partners have already a partner picked for them, the agent does not have a communication partner in that time turn of the simulated world.

If two agents are assigned to each other as communication partners in a time turn of the world, they use their language to communicate symbols aiming to achieve a decision about cooperation / defection. Following the reaching of this decision (as described above) the agents use their resources to generate new resources. If they both decide to cooperate, they pool together their resources and share equally the extra resources that they obtain in this way. If one agent cooperates and the other defects, they pool together their resources, but all extra resource is taken by the one that defects, while the cooperating agent does not get any extra resources and even looses a proportion ($\alpha = 0.05$) of the resources that they could generate individually. If both agents decide to defect then they generate their resources individually without pooling their resources and they do not lose any part of their individually generated resources. The new resource amounts are generated by sampling a normal distribution, for which the mean value is given as a function of the invested resources and the standard deviation is set as the uncertainty that characterises the simulated world of the agents. Thus, the new amount of resources may be more or less than the mean value that

Table 1. The pay-off matrix of the games played by the agents

		Agent 1	
		Cooperate	Defect
Agent 2	Cooperate	q, q	u, r
	Defect	r, u	v, v

directly depends on the invested resources and the extent to which differs from the mean value and the likelihood of such difference depends on the uncertainty of the simulated world. Formally, the game is represented by the pay-off matrix shown in Table 1 where $r > q > v > u$ and $2q \geq r + u$ and the pay-off values are the differences between the default amount of resource that the agent could generate by itself (i.e. without pooling resources with another agent) and the amount of resources that they can generate with the involvement of their partner agent. Thus, $v = 0$, $r = \Delta$, $q = \Delta/2$ and $u = -\alpha \cdot \rho'$, where ρ' is the amount of the resource that could be generated alone by the considered agent and Δ is the difference in the amount of resource that can be generated jointly by the agents and individually by them. The actual values of the generated resource amounts are taken as a sample from normal distributions. The mean value of the distribution for the resource amount that can be generated by an agent with available resources ρ is $f(\rho)$, while the mean value for the distribution for the resources that can be generated jointly by the agents is $f(\rho_1 + \rho_2)$, where f is a function which is convex for the range of resource values that are considered, i.e. $f(x + z) \geq f(x) + f(z)$. The standard deviation of the resource distributions is given by the product of σ, which characterises the uncertainty of the simulated world, and the length of the communications that the agents engaged in to reach their cooperation / defection decisions, i.e. the longer it takes to reach the decisions more uncertain it gets the new resource generation. If ρ'_1 and ρ'_2 are the resource amount samples that the agents could generate alone and $\rho'_{combined}$ is the resource amount sample for the joint resource generation, such that $\rho'_{combined} \geq \rho'_1 + \rho'_2$ (i.e. the samples are taken until the samples satisfy this inequality), then $\Delta = \rho'_{combined} - (\rho'_1 + \rho'_2)$. For the calculation of the mean values of the distributions we used the function

$$f(x) = \frac{1}{1 + e^{-x+\mu}} \tag{8}$$

such that the considered resource amounts are always on the convex part of the function (i.e. $\rho < \mu$). We note that as the resource game is set up, the Prisoner's Dilemma game conditions (i.e. inequality constraints among the pay-off values) are always satisfied.

The agents may engage in social learning by considering their best performing neighbour, in terms of available resources. If the best performing neighbour has more resources than the agent, then the agent may copy fully some of the language rules of the neighbour, i.e. by copying the probabilities for the language rule. The likelihood of copying a language rule is given by the extent of practicing social learning in the simulated world, η, which is set for the simulated world. After rules are copied the satisfaction of the intention consistency constraint is checked and if necessary probabilities for language rules are adjusted. We used $\eta = 0$ for simulations with no social learning and $\eta = 0.8$ for simulations with social learning enabled.

The agents spend their resources for their survival in each time turn of the simulated world. Agents for which the available resource amount drops below 0, die and no longer continue their existence in the simulated world. If an agent reaches the age of $T_{max} = 60$ time turns and they have accumulated resources, the agent produces a set of offspring and then dies. The offspring is produced in asexual manner. The new agents copy the language of their parent and share equally between themselves the resources of their parent agent. The number of offspring of an agent depends on the amount of resources that they have at the time of their death and it is calculated as

$$N_{new} = a \cdot \frac{\rho - \bar{\rho}}{\sigma_\rho} + b \tag{9}$$

where ρ is the amount of resources of the agent, $\bar{\rho}$ is the average amount of resources and σ_ρ is the standard deviation of resources across all live agents, a and b are parameters ($a = 1.5$ and $b = 1.75$ in the implementation of the simulated world), and the actual number of offspring is the integer part of N_{new}. Only agents for which $\rho > \bar{\rho}$ are considered for generation of offspring. The offspring start with randomly set ages between 1 and $T_{startmax} = 20$. The location of the offspring may originally be clustered at the location of the parent or alternatively the offspring may get spread around randomly in the simulated world. We explored both options in order to consider both the cases when potential collaborators / defectors can be easily identified (clustered offspring) and when this is not easily possible (spread out offspring).

Cooperation was measured as the proportion of agents that engaged in cooperation by jointly choosing the (h, h) communication symbols at the end of their communications with their partners. We also measured the proportion of defectors and of those who did not engage in joint resource generation, i.e. the equivalent of reaching the (t, t) communication symbols at the end of their communications with their partners or not having partners at all. We also measured correlates of cooperation such as the language uncertainty measures proposed above in terms of the average length of communications between agents and the standard deviations of distributions of communication continuation probabilities. For the latter, we considered all language rules and all probability values associated with these and calculated the standard deviations of the probability values across all live agents. Then we calculated the average of these standard deviations as a measure of the standard deviation of communication continuation probability distributions.

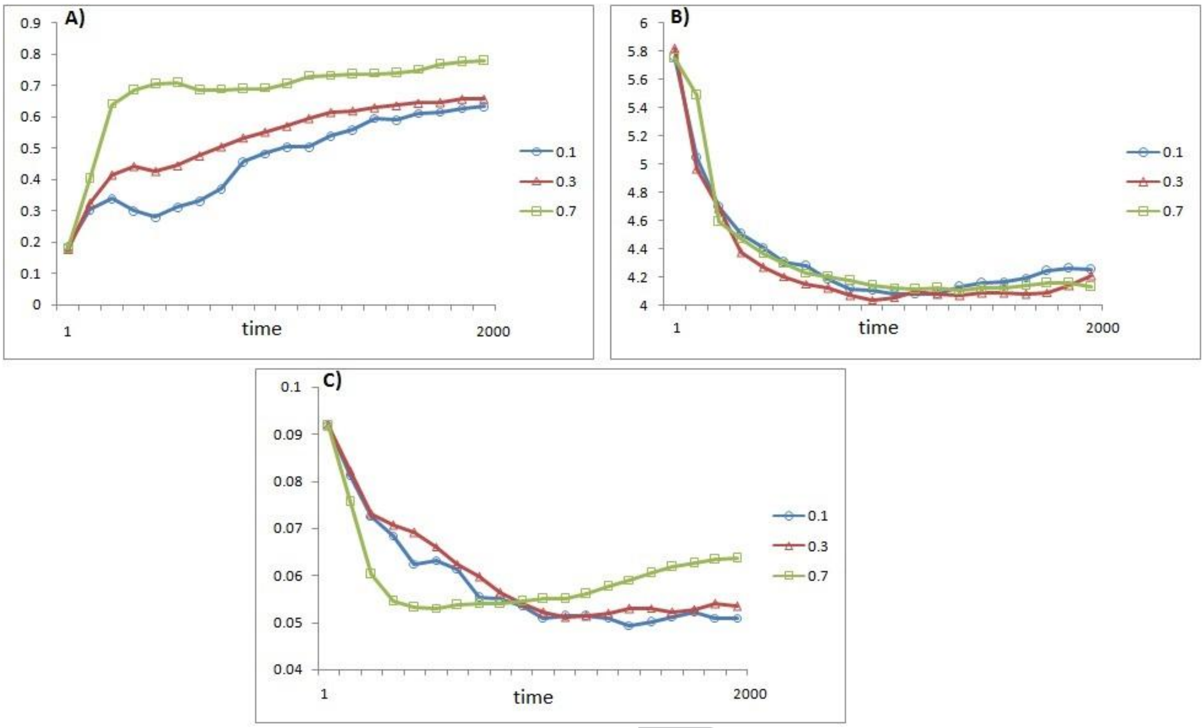

Figure 1. Evolution of cooperation in agent communities with clustered offspring and no social learning. The horizontal axes show time, while the vertical axes show: A) level of cooperation; B) average communication length; C) average standard deviation based language complexity. The levels of environmental uncertainty are shown in the legends and with lines with different colours and different markers.

6. Results and discussion

The agent's world simulations were run with and without social learning and also with clustered offspring and spread out offspring. We used three different levels of environmental uncertainty in the simulations, $\sigma = 0.1;\ 0.3;\ 0.7$. Each simulation of the agent's world ran for 2,000 time turns. For each simulation setting (i.e. with/without social learning, clustered/spread out offspring, level of uncertainty) we ran 20 simulations. The data reported in the paper are average values calculated over 20 runs. The standard deviations are considerably smaller than the average values and these are not included in the figures to avoid cluttering. The reported results include the proportion of cooperating agents (level of cooperation), the average length of communications and the average standard deviation of the distributions of the probability values of the communication language rules.

We found in simulations without social learning that more environmental uncertainty is associated with significantly higher level of cooperation among the agents (Figures 1A and 3A). In the case of presence of social learning and clustered offspring this differentiation is valid only in the earlier stage of the simulations, while later all simulations converge to high level of cooperation (Figure 2A). In the case of spread out offspring with social learning we found that the cooperation level associated with lower environmental uncertainty is higher than the level of cooperation corresponding to high

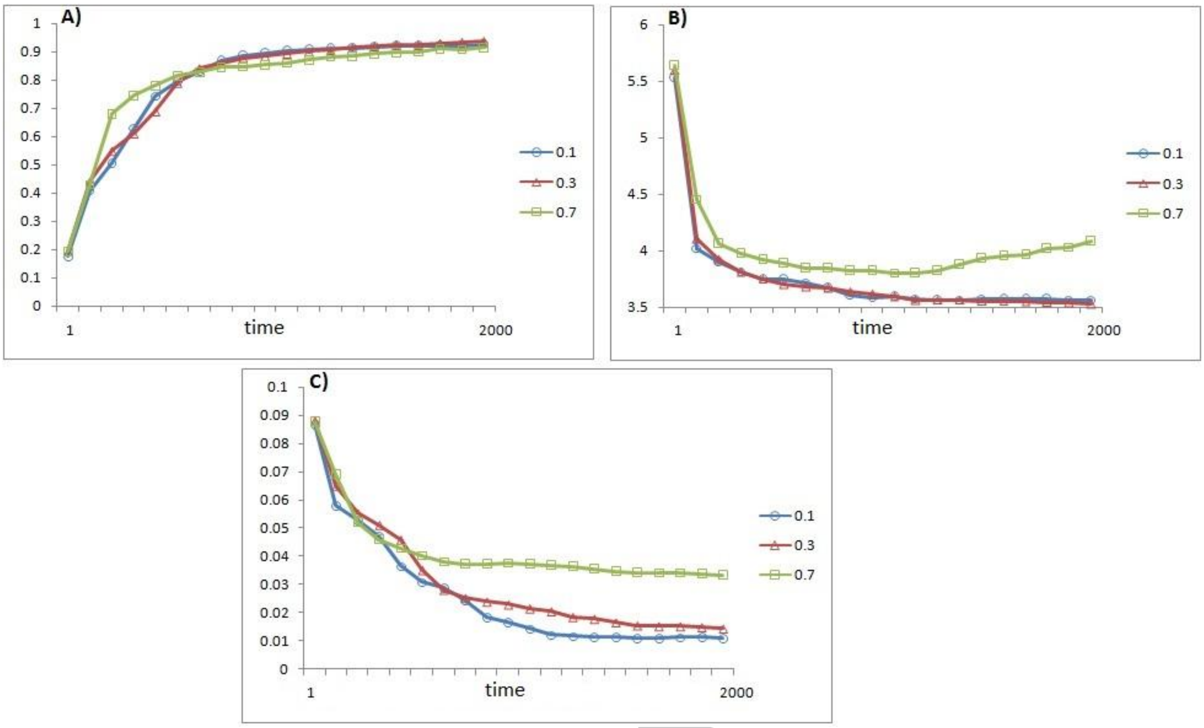

Figure 2. Evolution of cooperation in agent communities with clustered offspring and with social learning. The horizontal axes show time, while the vertical axes show: A) level of cooperation; B) average communication length; C) average standard deviation based language complexity. The levels of environmental uncertainty are shown in the legends and with lines with different colours and different markers.

level of environmental uncertainty (Figure 4A). This is consistent with findings reported in earlier papers (Andras et al, 2003; Andras et al, 2006; Andras, 2008; Andras, 2016).

In terms of average length of communications and average standard deviation of language rule probability value distributions our results expand on previously reported results (Andras, 2008; Andras, 2016) due to the longer simulation times (i.e. 2,000 time turns compared to previous reports based on 400 time turns). Similar to previous reports (Andras, 2008) we found that in the absence of social learning there are no significant differences in the evolution of the average length of communications due to different levels of environmental uncertainty with or without spreading of offspring (Figures 1B and 3B). However, in the presence of social learning the average length of communications is significantly higher in the long term in environments with higher uncertainty, both with and without spreading of the offspring (Figures 2B and 4B). In terms of the standard deviation based language complexity measure we found that in the short term higher environmental uncertainty is associated with lower language complexity, if there is no social learning and the offspring are clustered (Figure 1C) – this is similar to earlier reports (Andras, 2016). However this relationship gets reversed in the longer term and more language complexity is associated with higher environmental uncertainty. We found that in the long term, in the absence of social learning, the language complexity slowly increases after a rapid drop in the first quarter of the simulations (Figure 1C and 3C). In the absence of social learning and with spread out offspring, we found that the language complexity is initially higher for environments with high uncertainty, but in the long terms

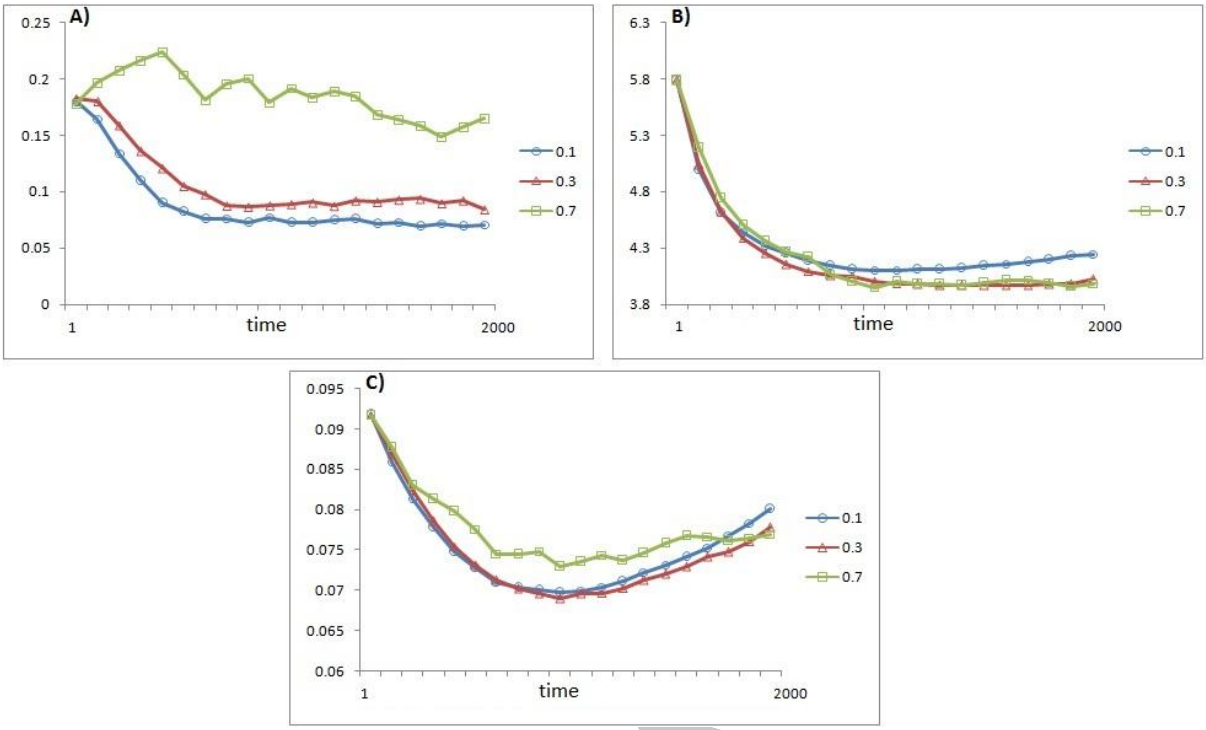

Figure 3. Evolution of cooperation in agent communities with spread-out offspring and no social learning. The horizontal axes show time, while the vertical axes show: A) level of cooperation; B) average communication length; C) average standard deviation based language complexity. The levels of environmental uncertainty are shown in the legends and with lines with different colours and different markers.

the language complexities become comparable for all considered levels of environmental uncertainty (Figure 3C). In the presence of social learning, with or without spreading of the offspring, the language complexity is higher for higher uncertainty environments and for all levels of environmental uncertainty the language complexity does not increase in the long term (Figure 2C and 4C).

Further we calculated the correlations between the level of cooperation, average communication length and standard deviation based language complexity for the later evolutionarily more steady part of the simulations (i.e. beyond 500 time turns). The results are shown in Table 2. At low levels of environmental uncertainty the reported correlations are strongly negative, with the exception of the case when the offspring is spread out and there is no social learning. At high level of environmental uncertainty some of the correlations are in line with correlations measured at lower levels of

Table 2. Correlations of the level of cooperation with language complexity based correlates of cooperation

Environment	Clustered offspring No social learning		Clustered offspring Social learning		Spread offspring No social learning		Spread offspring Social learning	
Uncertainty	Comm Length	Lang Complex	Comm Length	Lang Complex	Comm Length	Lang Complex	Comm Length	Lang Complex
0.1	– 0.411	– 0.913	– 0.953	– 0.973	0.483	– 0.229	– 0.982	– 0.997
0.3	– 0.492	– 0.897	– 0.940	– 0.994	0.834	0.311	– 0.988	– 0.991
0.7	– 0.422	0.928	0.541	– 0.977	0.641	0.090	0.941	– 0.938

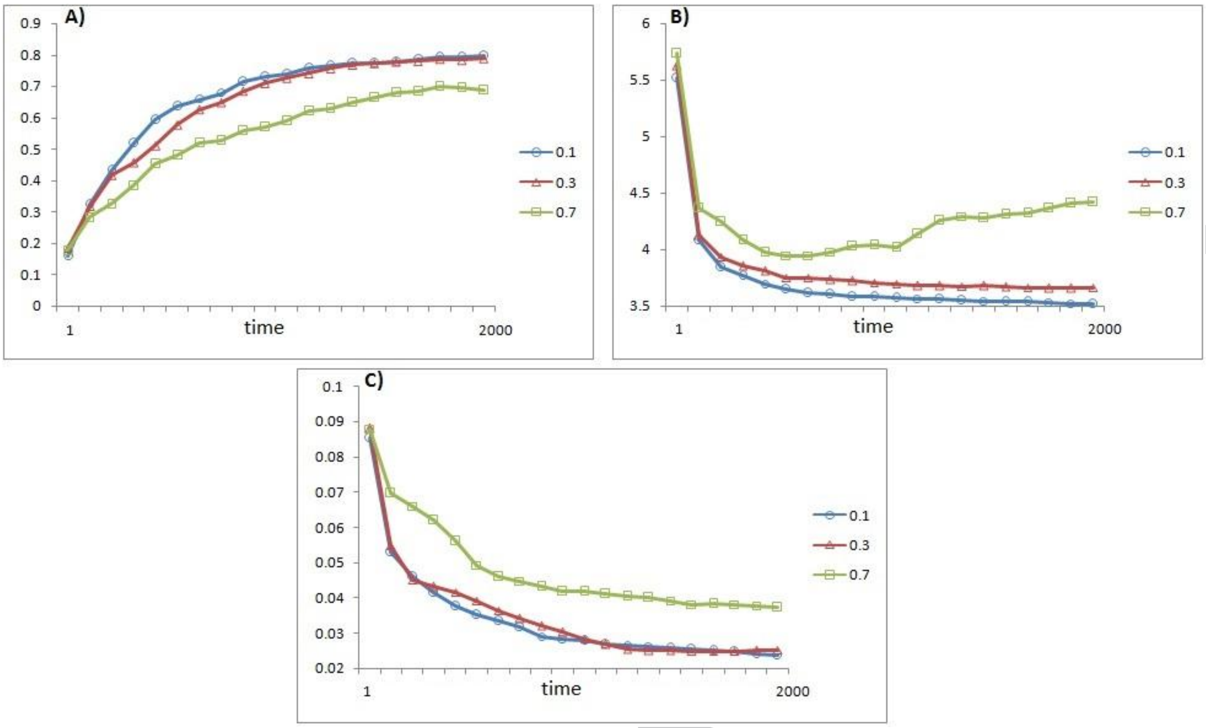

Figure 4. Evolution of cooperation in agent communities with spread-out offspring and with social learning. The horizontal axes show time, while the vertical axes show: A) level of cooperation; B) average communication length; C) average standard deviation based language complexity. The levels of environmental uncertainty are shown in the legends and with lines with different colours and different markers.

environmental uncertainty, however there are some very significant exceptions, the correlation with the standard deviation based language complexity is strongly positive in the case of clustered offspring and no social learning and the correlation with the average communication length is strongly positive for the cases of social learning both with clustered and spread out offspring.

To assess the impact of social learning we considered the differences between the evolution trajectories of cooperation level, average communication length and standard deviation based language complexity for simulations with and without social learning, and separately for the simulations with and without spreading of the offspring. We found that social learning increases significantly the level of cooperation and this effect is much more pronounced at lower level of environmental uncertainty (Figure 5A and 6A). The data shows that this effect increases with time if the offspring are spread out (Figure 6A), but in the case of clustered offspring the effect is larger in the earlier stage of the simulation and then it gets slightly reduced in the long term (Figure 5A). Social learning reduces significantly the average communication length in the early stage of all simulations, however, in the longer term this effect gets reduced for all levels of environmental uncertainty, and in particular in the case of high environmental uncertainty (Figure 5B and 6B). In the case of spread out offspring and high environmental uncertainty the average communication length increases in the long term in the presence of social learning (Figure 6B). We found that social learning reduces the standard deviation based language complexity measure both for simulations

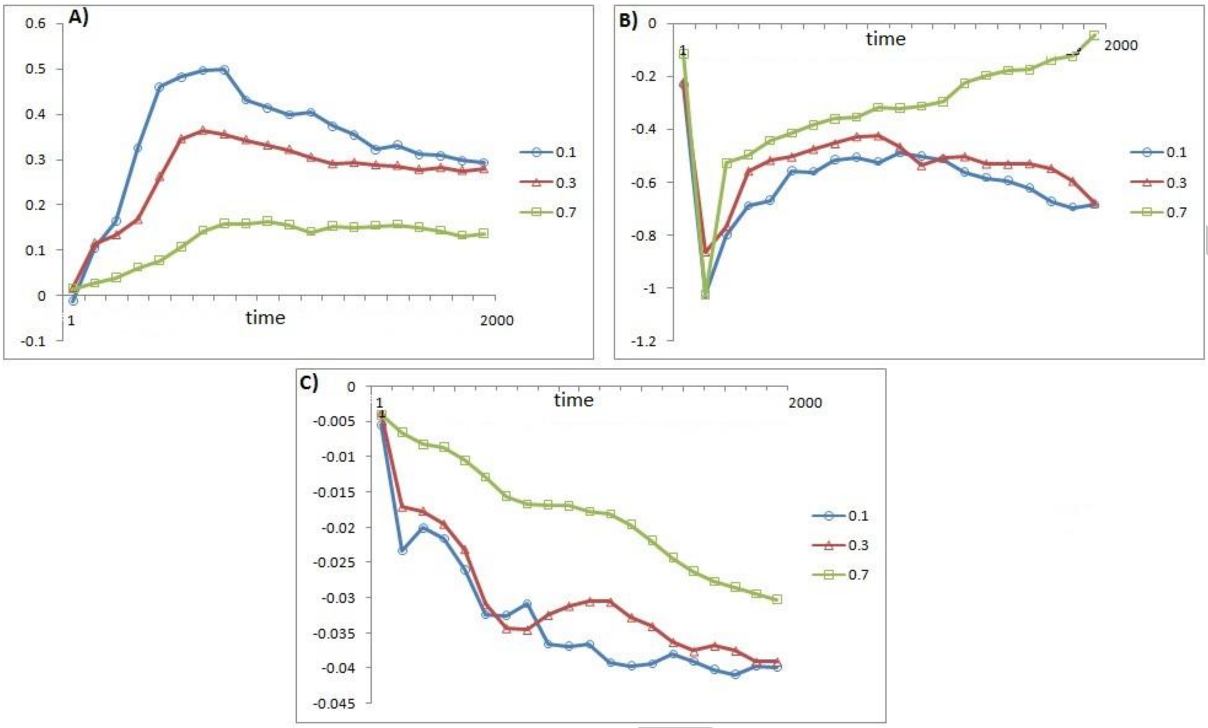

Figure 5. The difference caused by the presence or absence of social learning in the evolution of the cooperation in agent communities with clustered offspring. The horizontal axes show time, while the vertical axes show: A) level of cooperation; B) average communication length; C) average standard deviation based language complexity. The levels of environmental uncertainty are shown in the legends and with lines with different colours and different markers.

with clustered and spread out offspring (Figure 5C and 6C). This effect is more significant for lower levels of environmental uncertainty.

Overall we found that at lower levels of environmental uncertainty the language complexity metrics correlate strongly negatively with the level of cooperation, with the exception of the case of spread out offspring with no social learning. The presence of social learning makes these negative correlations more pronounced at low levels of environmental uncertainty. These indicate that if social learning is present or if the identification of possible cooperation partners is easier (i.e. clustered offspring) the considered language complexity correlates of cooperation are valid indicators of the latter in the context low environmental uncertainty.

Social learning is more effective in promoting cooperation at lower levels of environmental uncertainty. Social learning is in particular effective in driving cooperation higher in the context of spread out offspring, i.e. in cases when identification of likely cooperation partners is more difficult. This suggests that in the context of social institutions in low uncertainty environments social learning (copying of other's behaviour) is likely to contribute very much for the maintenance of cooperative behaviour. The results also suggest that the effect of social learning in such institutions may be replaced to some extent by the easier identifiability of potential cooperation partners, e.g. membership of informal groups, formal or informal associations. Furthermore, the results indicate that in the lack of easy identification of possible cooperators and in the absence of common

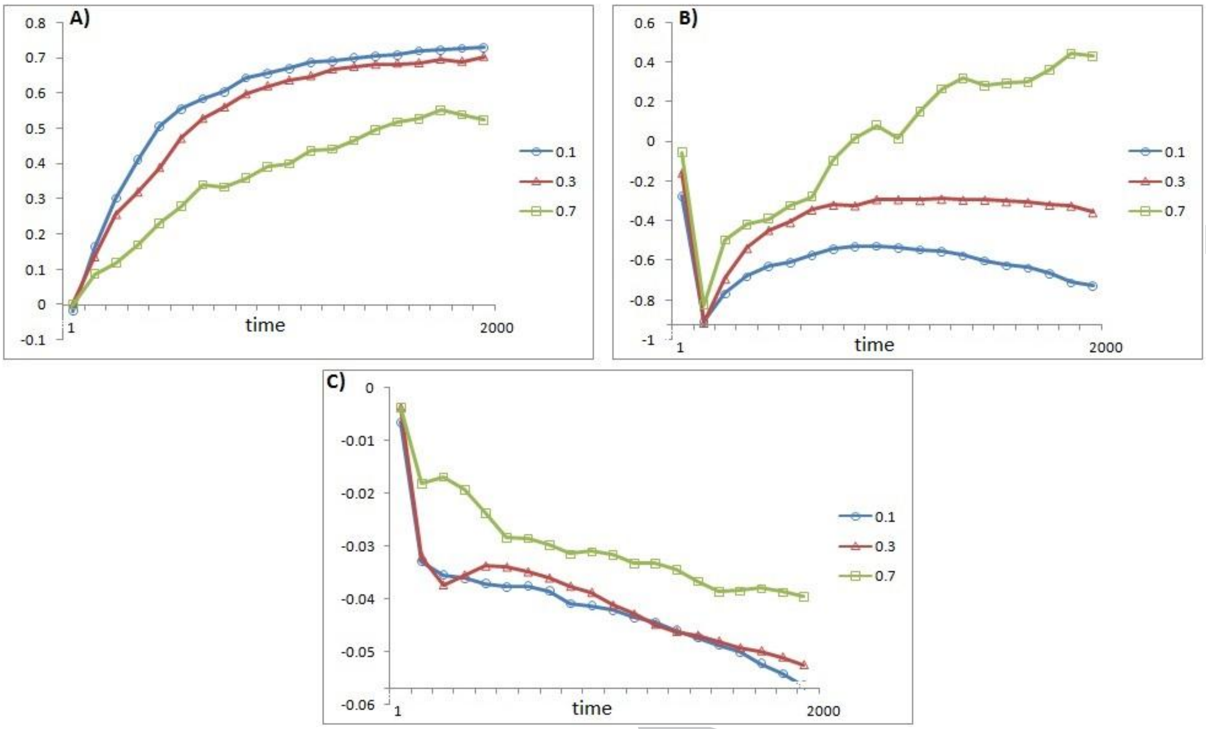

Figure 6. The difference caused by the presence or absence of social learning in the evolution of the cooperation in agent communities with spread-out offspring. The horizontal axes show time, while the vertical axes show: A) level of cooperation; B) average communication length; C) average standard deviation based language complexity. The levels of environmental uncertainty are shown in the legends and with lines with different colours and different markers.

practices of social learning the level of cooperation in an institutional environment is likely to be very low. This in turn may undermine the existence of the institution.

In general higher level of environmental uncertainty promotes more cooperation. Interestingly, the impact of social learning on the level of cooperation in high uncertainty environments is reduced compared to this impact in lower uncertainty environments. We also found that the language complexity correlates in high uncertainty environments behave differently from the case of low uncertainty environments. Social learning makes the behaviour of the language variability in the context of high uncertainty environments similar to the case of low uncertainty environments, however in terms of communication length the effect is rather the opposite. This suggests that presence of social learning in institutions in high uncertainty environments reduces the variability of the ways how language is used within the institution. However, the length of negotiations and interactions that lead to cooperative behaviour are likely to get extended, especially in cases where the identification of trustworthy cooperation partners is not easy. Lengthier negotiations provide more opportunity for the signalling of cooperation intentions and in an institutional environment may also lead to the emergence of novel forms of communications, i.e. the equivalent of adding symbol innovations to the communication language used to negotiate about cooperation / defection.

The higher language variability and average communication length in high uncertainty environments compared to low uncertainty environments (most of the reported cases) and the positive correlations of these with the level of cooperation in some of the reported cases are somewhat puzzling. These results suggest that in institutions operating in high uncertainty environments higher variability of the language is maintained because successful performance may depend more on external uncertainties and thus patterns of behaviour (including institutional language usage) that are associated with success are more variable. Thus external uncertainty induces the maintenance of internal uncertainty, which may also provide an adaptive advantage, since the institution retains variability of practices making it able to respond adaptively to variable external conditions.

The results presented here suggest that high environmental uncertainty promotes cooperation and through this the strengthening of institutions. On the other hand social learning promotes strengthening of institutions through cooperation most strongly in low uncertainty environment. These imply that institutions may emerge in environments that present high uncertainty in some respect. In this context the institution emerges as a cooperation game that can reduce the perceived uncertainty of the individuals. As the operating institution reduces the perceived uncertainty social learning may take its turn and improve the level of cooperation in the same or other related institutions. Mechanisms of identification of likely cooperators may also emerge, replacing to some extent the need for generalised social learning for the promotion of cooperation in the institution. The stable institutional environment allows exploration of new areas and aspects of the environment, where new uncertainties may get discovered triggering further institution emergence. Thus environmental uncertainty, social learning and easier identification of cooperation partners may work as alternating mechanisms for the triggering and development and expansion of the institutional environment. The partial equivalence of the effect of social learning and easy identification of cooperators means that these two mechanisms may work in a complementary manner. However, expansion of the easy identification of cooperators may actually reduce the general social learning within the institution, which in turn may limit the growth potential of the institution.

The above scenario is interesting and seems plausible, however so far neither the simulations reported here or other similar simulation based studies managed to actually simulate the emergence of new institutions. The work presented here provides the grounds for this next step of research. Institutions can be represented abstractly as cooperation games. Then the mechanisms of environmental uncertainty, social learning, easy identification of cooperation partners combined with the perception of experienced uncertainty and exploration for discovery of new games may combine such that the suggested model of institutional emergence and evolution may be implemented. In some sense the existence of efficiently working institutions creates the new opportunities for institutions formation by creating new potentials for resource generation in uncertain environments. However currently it is not clear how this could be incorporated into simulations of institutional evolution.

Another future research direction is the simulation of the expansionary evolution of the language though agent-based simulation studies. While various language evolution simulations are based on versions of naming games (Centola and Baronchelli, 2015; Steels, 2015), these do not link to studies on evolution of cooperation and of the institutional environment. At the same time it is likely that language evolution is closely related to the institutional evolution of the environment of the language. In the above note about possible ways to simulate institutional evolution it is assumed that any new institutional game is given with an appropriate associated language. An alternative is to discover the new institutional game through gradual additions to and evolution of the language until it can capture the new institutional game. This has not been done so far, but the work reported here may provide the required foundation for this. Language expansion mechanisms may be added, e.g. adding of new symbols, splitting of existing symbols, constraining and expanding the set of possible follow-on symbols, which may allow to expand initially the language used for playing of a given game and then possibly to spin-off a sub-set of the language to play a new institutional game (as an example we may consider the elaboration of behavioural fighting games among animals, which may lead to the emergence of other collaboration games that may become useful in hunting for resources or group-against-group fights).

7. Conclusions

The paper reports on agent-based modelling experiments aimed to explore the role of social learning for the evolution of cooperation in communities of selfish-agents in the context uncertain environments. The results show that social learning in general is beneficial for the increase of cooperation and this effect is most pronounced in low uncertainty environments. The results also show that the other two factors that we have considered through the simulations, the level of environmental uncertainty and the clustering / spreading of offspring of agents (considered an implementation of the easy / difficult identification of potential cooperation partners), have significant influence on how cooperation evolves.

We conceptualised cooperation games as abstract representations of institutions. The simulation environment allowed us to explore language complexity metrics as correlates of the level of cooperation. Our results show that the language complexity metrics have a partly different relationship with the level of cooperation in low and high uncertainty environments. The results also show that social learning leads to relatively higher level language complexity in high uncertainty environments compared to low uncertainty environments, and may also support the increase of language complexity in the long term, when this is measured as the length of communications between agents. In the context of the institutional interpretation of cooperation games, this implies lengthier negotiations about cooperation / defection decision choices, more adaptability to address uncertain environmental opportunities, and opportunities for the emergence of communication language innovations.

We suggested that environmental uncertainty, social learning and identification of likely cooperation partners may act as alternating mechanisms that support increasing levels of cooperation and effective operation in institutions. In the first instance the environmental uncertainty experienced in the context of an institution representing cooperation game leads to increased cooperation and institutional efficiency. Following the reduction of perceived uncertainty social learning and easier cooperator identification may lift further up the level of cooperation and institutional efficiency. In turn new uncertain games and corresponding institutions may get established, where again uncertainty takes its turn to drive up cooperation and institutional efficiency. Naturally, all these are expected to apply in competitive settings.

We noted that future work may focus on expansion of the current simulation environment in two possible directions. One is towards the exploration of language evolution in the setting of institutional cooperation games, which may lead to the implicit discovery of novel institutions and corresponding cooperation games. The other direction is towards the investigation of institutional evolution through the mechanisms considered here combined with expanding experienced uncertainty and discovery of new institutional games, where new institutions are assumed to be discovered together with their associated communication language.

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HIGHLIGHTS

Social Learning in Repeated Cooperation Games in Uncertain Environments

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- Uncertainty, social learning and identification of likely cooperation partners contribute in turns to maintenance and expansion of social institutions.
- Social learning is most beneficial in the context of low uncertainty environments.
- Language complexity metrics negatively correlate with the level of cooperation in low uncertainty environments.
- High uncertainty drives higher the level of cooperation.