Uncertainty and communication complexity in iterated cooperation games

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Abstract

Iterated cooperation games (e.g. Prisoner's Dilemma) are used to analyze the emergence and evolution of cooperation among selfish individuals. Uncertainty of outcomes of games is an important factor that influences the level of cooperation. Communication of intentions also has a major impact on the outcome of situations that may lead to cooperation. Here we present an agent-based simulation that implements the uncertainty of outcomes together with the communication of intentions between agents. This simulation is used to analyze the relationship between uncertainty and the complexity of the language that the agents use to communicate about their intentions. The complexity of the language is measured in terms of variability of its usage among agents. The results show that more outcome uncertainty implies lower complexity of the agent language.

Introduction

Iterated cooperation games are commonly used to study the emergence and evolution of cooperative behaviour in communities of selfish individuals (Axelrod, 1997). Such games, especially ones that have a non-cooperative single play equilibrium (e.g. Prisoner's Dilemma game (Axelrod, 1997)) can simulate the selfish drive of individuals and offer a natural experimental environment to analyse the effects of various factors on cooperative behaviour.

The main theories about the emergence of cooperation consider as key factors the similarity (relatedness, kinship, joint interest) of individuals and the direct/indirect reciprocity of their behaviour (Axelrod and Hamilton, 1981; Leimar and Hammerstein, 2001; Nowak and Sigmund, 1998; Riolo et al., 2001; Rockenbach and Milinski, 2006; Roberts and Sherratt, 1998; Trivers, 1971). Other important factors include commitment inertia (Roberts and Sherratt, 1998) and segregation of cooperators (Pepper, 2007). Most of these theories assume repeated interactions between the same individuals and/or interactions between all possible pairs of individuals (Axelrod, 1997). These theories also assume well defined outcomes of the played games and usually pay little attention to communicative behaviour of individuals participating in game playing (Axelrod, 1997).

In real life situations the outcomes of cooperation or defection usually are uncertain and depend on many other factors outside of the control of the interacting individuals (Callaway et al., 2002; Pulford and Coleman, 2007; Seghers, 1974; Spinks et al., 2000). Communication between individuals is an integral part of the action selection and decision making process and consequently may matter very much during the interaction process (Dugatking, 1997; Dunbar, 1988). Individuals may try increase cooperation willingness in their partner through communication. They may also use communications to hide their true intentions. Earlier works show that indeed uncertainty of outcomes and communicated intentions may play an important role in determining the level of cooperation in communities of selfish individuals (Andras et al., 2007; Andras et al., 2006; Andras et al., 2003).

Anecdotal evidence suggests that experienced uncertainty, due to the environmental context, has the effect of reducing the complexity of the communication of intentions. For example, surgeons use very restricted language to communicate during operations, the restrictions of the language being aimed to reduce uncertainty and the possibility of misunderstandings in a very uncertain environment (i.e. there may be many unexpected complications during the surgical operation). Another example is the army, where again the communication of orders is done in a highly simplified language, again aimed to reduce uncertainty in the interpretation of orders in the context of a highly uncertain environment (where the soldiers may encounter many unexpected situations created by their enemy).

Here we describe a simulation study aimed to analyse and quantify the effects of uncertainty on communication complexity in the context of situation where cooperation emerges and is maintained in a community of agents. In the agent-based simulation study the agents played Prisoner's Dilemma games. The study confirms the expectation based on the anecdotal evidence, i.e. that more experienced uncertainty implies more reduction in the complexity of the communication language that agents use to communicate their intentions during their interactions. This result helps the understanding of the evolution of the language that is used as medium of interactions between individuals in the context of potentially cooperative social interactions.

The rest of the paper is structured as follows. First we discuss the concept of uncertainty in the context of cooperation games. Next we consider the role of communication of intentions between individuals playing cooperation games. This is followed by the discussion of communication complexity. Next we describe the agent-based simulation environment that we used for our study. This is followed by the presentation of the results of the simulation study. Finally, we end the paper with our conclusions.

Uncertainty in cooperation games

The usual setting of agent-based simulations with iterated cooperation games assumes that the possible outcomes of games are known and fixed across all games played during the simulation (Axelrod, 1997). This assumption is useful to keep the games and the simulations analytically tractable. However, this assumption is frequently not satisfied in real life situations that are modelled by such games and simulations.

In real life situations the more usual is that the outcomes of games vary around some expected outcome. The amount of variation differs from case to case. If the variation is small the situation and its possible outcomes are relatively certain, for example in case of interactions which lead to a contract defining obligations of the parties that determine the outcomes of the interaction (or game). If the variation of outcomes is high the situation and its outcomes are uncertain, for example when army troops are advancing on unknown enemy territory, interactions between soldiers may have widely varying effects.

Uncertainty of outcomes can be represented in a straightforward way in cooperation games by replacing the fixed outcomes by outcome distributions (Andras et al 2007). For example, Table 1 represents a fixed outcome cooperation game.

		Player 1	
		Cooperate	Defect
Player 2	Cooperate	R,r	s,t
	Defect	T,s	p,p

Table 1: A fixed income cooperation game

The letters r, t, s, p stand for: 'reward for cooperation', 'temptation to defect', 'punishment for joint defection' and 'sucker's payoff'. To include the representation of outcome uncertainty the values r, t, s, p are replaced by (normal or exponential) distributions R, T, S, P such that the mean value of these distributions is the corresponding fixed outcome, while the variance of the distributions represents the uncertainty of the game outcomes. When players play the game they pick first their distribution according to their game playing choice and then they pick their actual outcome from this distribution by taking a random sample from the distribution. In average the outcomes of many games will be close to the fixed outcome approximation of the game, but considering outcomes of individual games they will be distributed according to the adopted distributions with a variance corresponding to the uncertainty of the game.

It has been shown that uncertainty in the outcomes of games (due to environmental factors) influences the level of cooperation in the context of agent-based simulations of iterated cooperation games with uncertain outcomes (Andras et al., 2007; Andras et al., 2006; Andras et al., 2003). The stable level of cooperation within a population of agents increases as the uncertainty of the outcomes of the games played by agents increases (Andras et al., 2007). This is consistent with a range of observations of natural situations where the uncertainty imposed by the environments induces more cooperative behaviour among bacteria (Drenkard and Ausubel, 2002; Mehdiabadi et al., 2006), plants (Callaway et al., 2002), and animals (Seghers, 1974; Spinks et al., 2000; Kameda et al., 2002).

Communication of intentions

Commonly agent-based simulations of emergence and evolution of cooperation use cooperation games where the communication between agents is compressed into a single-shot communication expressed by the game playing choice of the agent (Axelrod, 1997). This excludes the communication of intentions or provision of cues about intentions that may influence the other player. However, in real world situations such communications play a critical role in the development of interactions between individuals (Drenkard and Ausubel, 2002; Dugatking, 1997; Dunbar, 1988). (Note, that while in the literally understood Prisoner's dilemma situation there is no possibility of communications, in many situations analysed using this model of interaction there is an important role for communication of intentions.)

It is crucial to include into agent-based simulations the communication of intentions to understand how real world cooperation works. Including communications about intentions may also allow the study of the role of trust and deception in the emergence and evolution of cooperation.

Representing communication of intentions is not trivial in the context of agent-based simulations. To do this the agents have to be equipped with some form of communication language which relates to intentions of the agents and allows the communication about these intentions (exposing or hiding them) in a consistent manner. One way to achieve this is to define the language of agents in the form of a probabilistic grammar with two parallel inputs (Andras, 2003). This grammar can be described using production rules of the form

$$u_{current}, u'_{current} \rightarrow \{u^1_{next} : p_1, \ldots, u^k_{next} : p_k\} \quad (1)$$

Where $u_{current}$ is the last communication symbol produced by an agent, $u'_{current}$ is last communication symbol produced by the interaction partner of the agent, $u^1_{next}, \ldots, u^k_{next}$ are the next communication symbols that can be produced by the agent, and $p_1, \ldots, p_k$ are the probabilities of production of these communication symbols,

$$\sum_{j=1}^{k} p_j = 1 \quad (2)$$

The grammar should include communication symbols representing the start of the communication and symbols representing the play choice of the agents (cooperate or defect). Other symbols may have various semantics depending on the intended semantic extent of the language (e.g. the aim may be inclusion of modeling of trust).

The rules of the language should be such that they are consistent with the practice of communication of intentions in the case of biological organisms. In particular, signs of positive intentions are usually followed by signs of similarly or more positive intentions. Such consistency rules should be implemented in the language of agent communications by imposing consistency constraints on the transition probabilities. The positivity of a communication symbol is given by the level of pro-cooperation intention (positiveness) indicated by the symbol when it is produced during communication. To express the above rules more formally, if u_0, u_1, u_2, u_3 are communication symbols, such that their positivity ranking is

$$u_1 \leq u_2 \leq u_3 \tag{3}$$

and u_3 can be produced according to production rules

$$u_1, u_0 \rightarrow u_3 : p_1 \tag{4}$$

and

$$u_2, u_0 \rightarrow u_3 : p_2 \tag{5}$$

where p_1, p_2 are the probabilities of application of these rules then

$$p_1 \leq p_2 \tag{6}$$

In other words, more positive symbols are more likely to be followed by even more positive symbols than less positive symbols. Similarly, if the production rules are

$$u_0, u_1 \rightarrow u_3 : p_1 \tag{7}$$

and

$$u_0, u_2 \rightarrow u_3 : p_2 \tag{8}$$

and (3) holds, then again (6) holds, i.e. the same rule applies if the symbols with different positiveness are produced by the communication partner.

Communication complexity

Communication complexity can be defined using the concepts of Kolmogorov complexity (Li and Vitanyi, 1997). The complexity of a description is given by the length of the description. The complexity of a language can be considered in terms of the average length of non-interrupted communications in that language. Of course, this is a relatively rough measure of description and language complexity, but it can be used reliably, assuming no intention aimed to distort the measured complexity. A better approximation of description or language complexity, perhaps, is to consider the description length after the elimination of redundant and irrelevant components from the description or communications. Of course, this may inject some subjective bias into the measurement. In the case of an agent-based simulation with communication of intentions the above defined complexity of the agent language can be measured as the average length of communications between agents that last from the start of the interaction until the decision about the game choice.

An alternative way to measure the complexity of the language is to look at the variability of the language rules used by various individuals. If the rules contain high variability, i.e. there are relatively large differences in the way language rules are used, that indicates high complexity of the language (indirectly indicates high dependence of the rule use on the context of the use). Consistent regular application of language rules without much variation implies lower complexity of the language (i.e. less context-dependence). This alternative approach of measuring complexity of the language fits with the concept of Kolmogorov complexity in the sense that low variation of language rules means that the language can be described listing its rules and relatively few additional meta rules about the context-dependent application of the listed basic rules – i.e. the description of the language is relatively short. In the case of high variation of rule application, the language can be described by listing its basic rules and adding many meta rules about the context-dependent application of basic rules – i.e. the description of the language becomes relatively long. In the case of an agent-based simulation with communication language the measurement of complexity of the language according to this method involves the measurement of the variance of distributions of probabilities of grammar production rules. Higher variance in average across all rules means more variable application of the language and a more complex language. On the other end, lower variance in average means lower variability in language use and lower language complexity.

In the real world high uncertainty situations appear to be associated with low complexity communication languages (e.g. surgical theatre, army – see examples in the Introduction). Generally, the higher lexical complexity and higher complexity of application of rules of a language implies more uncertainty about what is communicated using the language. The uncertainty implied by the complexity of the language adds to the uncertainty imposed by the environment.

On the basis of observation of the link between experienced uncertainty and level of cooperation in communities of selfish individuals we expect that if the community experiences high uncertainty then the possible ways to deal with this is either to have high level of cooperation or to have low level complexity of the communication language, or some combination of these. Earlier work shows that the level of cooperation increases with the level of experienced uncertainty. Similarly we expect that in accordance with anecdotal evidence, the level of complexity of the language should decrease as the experienced level of uncertainty increases.

Simulation implementation

The agents 'live' in a two-dimensional rectangular world, which is wrapped on both pairs of edges (up and down, right and left). A position in the world may be occupied by more than one agent, and positions of agents can be arbitrarily close (i.e. the world is not divided into a grid of disjoint places). The dimensions of the world are set to be 100 x 100.

The agents in the simulation own resources, which are used to maintain themselves and to generate new resources alone or through interaction with another agent. In each time turn each agent tries to choose an interaction partner. The partner is chosen from those agents, which are located close enough (i.e. in the neighbourhood) to the agent which is looking for a partner. An agent may be chosen as a partner if the agent is not already partnered up with another agent. An agent may remain without a partner in a time turn if it cannot find any agent in its neighbourhood which could become its partner. The neighbourhood of an agent is defined as the set of ten closest agents, where the distance between agents is measured in the two-dimensional world populated by the agents.

After finding a partner the agents play a Prisoner's Dilemma type game with uncertain outcomes. The uncertainty of outcomes represents all uncertainties that may influence the interaction between the agents. The outcome uncertainty is implemented as described in the section 'Uncertainty in cooperation games'. For the sake of simplicity we use normal distributions characterized by a mean value and a variance. Playing the game determines the mean value of the distribution, while the variance of the distribution (σ) is a set value that characterizes the outcome uncertainty of the game. Note that our simulation implements iterated game playing without the requirement that the repeated games should be between the same agents, and in fact it is more likely that agents will play with many other agents during their 'lifetime'.

The agents participate in the game with their available resources, which determine the mean value of the outcome distribution. The function determining this mean value is

$$f(R) = a \cdot \frac{1}{1+e^{-R+R_0}} \tag{9}$$

where a and R_0 are parameters and Ris the amount of available resources. The parameters are set such that the game operates on the convex diminishing return part of the function where

$$f(2x) \geq 2f(x) \tag{10}$$

In order to preserve the Prisoner's Dilemma conditions (i.e. t>r>p>s and 2r>t+s) the game matrix determining the mean values of outcome distributions are set as in section 'Uncertainty in cooperation games' with the values

$$r = f(R) + \frac{\Delta}{2} \tag{11}$$

$$t = f(R) + \Delta \tag{12}$$

$$s = \alpha \cdot f(R) \tag{13}$$

$$p = f(R) \tag{14}$$

where

$$\Delta = \left[f(R_1 + R_2) - f(R_1) - f(R_2) \right]_+ \tag{15}$$

(i.e., it takes only the positive values of the expression in brackets and it is zero if the value of the expression is negative), $0<\alpha<1$ is a parameter.

After determining the mean values of the outcome distributions for both agents, they pick an actual outcome value from the normal distribution determined by this mean value and the variance σ that characterizes the outcome uncertainty of the world of the agents. The actual outcome values will be the new amount of resources available for the agents. Note that the actual outcome value may be below or above the mean value given by the game matrix. If the outcome uncertainty is high (i.e. σ is large) the likelihood of getting much more or much less than the mean value is relatively large. If the outcome uncertainty is low (i.e. σ is small) in most cases the actual outcome value will be close to the mean value determined by the game matrix.

The agents communicate using a simple language. The aim of this communication is to decide how to play the game. The lexicon of the language consists of the symbols: '0','s','i','y','n','h' and 't'. These symbols have the following meanings: '0' – no intention of communication, 's' – start of communication, 'i' – maintaining the communication, 'y' – indication of the willingness to engage into possible cooperation, 'n' – indication of no further interest in communication, 'h' – cooperation (ready to share the benefits of joint use of resources), 't' – cheating (ready to steal the benefits of possible joint use of resources). The last two symbols, 'h' and 't' represent the actual cooperation and defection game choices. The first four symbols are ranked according to their positive contribution towards engagement in cooperation (the least positive is the '0' and the most positive is 'y', '0'≤'s' ≤'i'≤'y').

Each agent has its own realization of the language. The language is represented in the form of a two-input probabilistic production rules according to equations (1) and (2). The implemented simple language contains 22 production rules. The probabilities associated with the production rules may differ between agents, representing the individual realization of the language. For example a probabilistic production rule is

$$i, i' \rightarrow \{y:0.3, i:0.5, n:0.2\} \tag{16}$$

that means that after producing the symbol 'i', and receiving a symbol 'i' from the communication partner, the agent will produce the symbol 'y' with probability 0.3, the symbol 'i' with probability 0.5, and the symbol 'n' with probability 0.2. The probability of the symbol pair ('y','y') being followed by the generation of the symbol 'h' is given by the intention to cooperate of the agent – I_{coop}. The individual realizations of language rules always satisfy the consistency constraints defined by equations (3) – (8).

After selecting an interaction partner the agents may engage in a communication process. The communication process starts properly after both agents communicated the 's' symbol. We set a limit (L_1) for the preliminary communication (i.e. before communicating 's' from both sides). If two agents do not reach the proper start of the communication in a communication of length L_1 they stop further communication and decide to choose play defection in their current game.

The agents use their own realization of the common language to produce communication symbols. The communication process ends either with the communication of an 'n' symbol (i.e., signaling no further interest), or with the communication of the 'y' symbol by both partners (or by automatically stopping the communication according to the set rules). After this each agent decides whether to cooperate or defect by producing the symbol 'h' or 't'. We impose a communication length limit (L_2) on this second stage of communication. If the agents do not reach the communication of 'y' symbols in L_2 steps, they stop their communication and decide to play defection in the current game.

During each communication process, as an agent produces equally or more positive symbols their intention to cooperate increases. The intention to cooperate of the agent increases temporarily and the increased intention of cooperation is valid only for the current communication process. The upgrade equation of the intention to cooperate is

$$I_{coop}(t+1) = 1 - (1-\delta) \cdot (1 - I_{coop}(t)) \tag{17}$$

where $I_{coop}(0)=I_{coop}$, t is the counter of communication symbols produced by the agent so far within the current communication process, and δ is a parameter (δ=0.025).

At the end of each time turn the agents make a random move, i.e. their position is updated according to the equation

$$(x_{new}, y_{new}) = (x, y) + (\xi_x, \xi_y) \quad (18)$$

where (x,y) is the old position of the agent, (x_{new}, y_{new}) is the new position of the agent, and (ξ_1, ξ_2) are random values from a uniform distribution over [-5,5].

The agents 'live' at most for 60 time turns. The agents may die earlier if they run out of resources. When they reach the end of their life they may produce a number of offspring agents. The number of these depends on the amount of resources owned by the agent, more resources implying larger number of offspring. If a dying agent has R amount of resources, and the mean amount of the resources in the agent community at that moment is R_m, and the standard deviation of resources is R_S, then the number of offspring of the agent is calculated as

$$n = \alpha \cdot \frac{R - (R_m - \beta \cdot R_s)}{R_s} + n_0 \quad (19)$$

where α, β, n_0 are parameters of the simulation environment. If n is negative or R=0 this means that the agent has no offspring. If $n > n_{max}$, where n_{max} is the allowed upper limit of offspring, the number of offspring is set to be n_{max}. The offspring of an agent inherit its resources divided equally between them. The locations of the offspring are set by a small random modification of the position of the parent agent.

When agents reproduce at the end of their life, their offspring inherits the language of the parent agent, possibly with some small random modifications of the language rule probabilities. This means that the offspring of an agent will speak the agent language in a very similar manner (using production rules with similar probabilities), which may facilitate cooperation interactions between them.

We ran 20 simulations for each level of outcome uncertainty. Each simulation ran for 400 time turns each time. Each simulation was initialized with 1500 agents with randomly set positions, initial resource amounts, and language transition probabilities.

To summarize, in each time turn the agents search for an interaction partner, and if they find one, they communicate about their intentions and play the above described game to generate their new resource amount. If an agent cannot find a partner it generates its new amount of resources as if it would be playing a defection/ defection game with another agent (i.e. the mean value of the resource value distribution from which it picks its new resource amount is set to be f(R), where R is the amount of its current resources). Agents move randomly at the end of each time turn and deduct from their resource amount a fixed amount of living costs. Agents may die because they run out of resources, or because they reach the end of their life (at most 60 time turns). When an agent dies and still has available resources, it may generate offspring, which will inherit its language with small variation. The offspring initially form a cluster around the place of their parent and gradually move away by random movements. (For more details about the simulation see Andras et al. (2003) and Andras et al. (2006). A version of the simulation code is available as online supplementary information for Andras et al. (2006). For further details and simulation code please contact the author.)

Uncertainty and communication complexity

In earlier work (Andras et al., 2007; Andras et al., 2006; Andras et al., 2003) we have shown that higher outcome uncertainty implies higher level of cooperation in agent populations. This is because the agents share their experienced uncertainty through cooperation, averaging the effective uncertainty that applies to their outcome. This means that through cooperation the effective uncertainty experienced by agents within the agent community is reduced compared to the individually experienced uncertainty that would apply to them without involvement in cooperative interactions (Andras et al., 2006). In order for the agent population to reproduce there is a critical level of outcome uncertainty, above which the population shrinks until it goes extinct. If the outcome uncertainty imposed by the environment is high, high level of cooperation is required to bring down the effective uncertainty to or below the critical level (Andras et al., 2006). Consequently, higher outcome uncertainty implies higher level of cooperation that is required to keep the population away from extinction. The current simulation confirms this earlier finding (see Figure 1). Note that this relationship between outcome uncertainty and the level of cooperation is valid even if there is no communication of intentions (Andras et al., 2007).

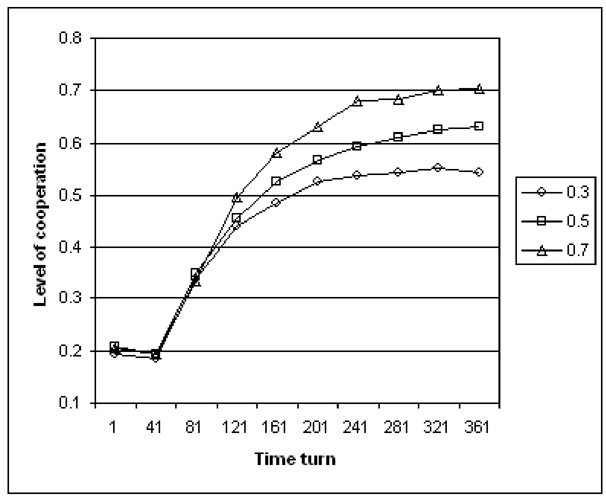

Figure 1: The relationship between outcome uncertainty and level of cooperation. The three lines show the evolution of the average level of cooperation across 20 populations of agents for three levels of outcome uncertainty (σ=0.3, σ=0.5, σ=0.7 – the box on the right indicates the corresponding lines). The level of cooperation is measured as the percentage of joint cooperation decisions among all game decisions made by agents in a given time turn. (Error bars are omitted as standard deviations are relatively small)

Here we investigate the relationship between the outcome uncertainty and the complexity of the language that the agents use. Our expectation is that higher outcome uncertainty implies lower language complexity. To measure the complexity of the language used by agents we adopt the approach introduced earlier based on the measurement of the variation of the use of the language rules. In other words, we measure the complexity of the language used within an agent population as the average of the variances of probabilities characterizing the production rules of the agent language. For each language production rule

$$R_i : u^i_{current}, u'^i_{current} \rightarrow \{u^{i,1}_{next} : p^i_1, \ldots, u^{i,k}_{next} : p^i_{k_i}\} \tag{20}$$

we consider all realizations of this rule (i.e. each realization is a realization of the rule in a 'living' agent) and calculate the variance for each involved probability p_1^i, …, p_k^i. Let us denote these variances as

$$\sigma^i_1, \ldots, \sigma^i_{k_i} \tag{21}$$

then the complexity of the language is defined as

$$cx = \frac{1}{K} \sum_{i=1}^{L} \sum_{j=1}^{k_i} \sigma^i_j \tag{22}$$

where L is the number of language rules (in the simulation we have 22 such production rules), and

$$K = \sum_{i=1}^{L} k_i \tag{23}$$

Using this measurement of language complexity we found that indeed higher level of outcome uncertainty implies lower level of language complexity in the context of our simulated agent communities. This result is presented in Figure 2. This confirms our expectation.

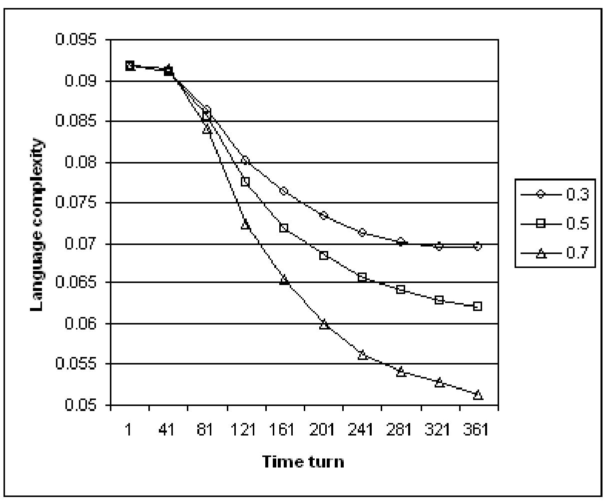

Figure 2: The relationship between outcome uncertainty and language complexity. The lines show the evolution of average language complexity across 20 populations of agents for three levels of outcome uncertainty (σ=0.3, σ=0.5, σ=0.7 – the box on the right indicates the corresponding lines)). The language complexity is measured according to equation (22). (Error bars are omitted as standard deviations are relatively small)

We also considered the alternative measure of the language complexity, i.e. the average length of communication processes that lead to the reaching of the cooperation / defection decisions. However this measure gives much less clear results, as the length of communication processes drops to around the same level (in average) at all considered levels of outcome uncertainty. The most likely reason for this is that the language is very simple and has very few communication symbols. Consequently, there is little variation that could exist in terms of communication process length between surviving agent communities 'living' in environments characterized by different outcome uncertainty. The language use variation based measure (the cx measure defined above) appears to be more sensitive to detect differences in language complexity between agent communities dealing with different levels of uncertainty.

The principial reason behind the observation of the lower language complexity in agent communities dealing with more outcome uncertainty is that lower language complexity adds less to the uncertainty of the world than higher language complexity, and consequently the lower language complexity is preferred in more uncertain environments. In practical terms, analyzing the evolution of simulated agent populations, we note that an important aspect is that surviving offspring of successful agents are clustered at the time of their creation. Having very similar language facilitates their continual success, especially if they inherited sufficiently cooperative inclinations from their parent. A more uncertain environment means stronger selection for successful individuals with relatively high cooperative inclination, which means that clusters of related agents have increased selection advantage in such environments. This is likely to contribute significantly to the reduction in the variability of the language usage that we adopted as a complexity measure of the language.

The presented results are about agent-based simulations. They confirm our expectation about the relationship between outcome uncertainty and language complexity and provide some explanation about why this is the case. However, to fully confirm our theoretical expectation about the effect of uncertainty on language complexity ideally we would need to consider real-world data. While it is not easy to find or collect relevant real-world data, we note that measurements of language diversity in naturally more and less uncertain areas of Africa (semi-desert in Northern Nigeria and rainforest in Burkina Faso) indicate that natural experimental confirmation of the presented results may be within reach (Nettle 1998; Nettle 1996). Nettle (1996, 1998) has shown that in the more arid and hostile semi-desert are the number of languages is much smaller than in comparable much less uncertain (in terms of availability of food) areas of rainforest. This appears to be in good agreement with our expectation and simulation results.

Measuring complexity of natural languages is not very obvious. We considered in this paper two measures and have shown that the one based on variability of language use seems to be more sensitive to measure complexity differences between agent languages. Applying similar measures to natural languages may lead to robust measures of language complexity. Our results indicate that language complexity is likely to be linked to the level of cooperativeness within a community. Consequently, analysis of complexity of language used for example in companies may help the understanding of the potential of the analyzed organization to deal with their experienced uncertain environment and to harness organizational resources that can be mobilized through cooperation.

Finally, we underline that our analysis and simulation is focused on the lexical complexity of the language used to inform about intentions (i.e. complexity in the sense of the variability of use of lexical components – communication symbols in the context of the simulations). We did not consider grammatical complexity (i.e. the number and combinatorial variability of rules), as in our case the number of rules is always fixed. A more extensive analysis of language complexity and more complicated simulation would be needed to consider aspects of grammatical complexity. We expect that losses suffered in terms of lexical complexity, imposed by the necessity of dealing with an uncertain environment, are compensated by increased complexity at the level of grammar in the longer run. The reason of this is that having more complex grammar increases the computational capacity of the language which may be beneficial in a more uncertain environment. This increase in grammatical complexity is supported by the decrease in lexical complexity in the sense that less ambiguity in the lexicon reduces the likelihood of inappropriate application of grammatical rules. The investigation of this conjecture is not the subject of this paper.

Conclusions

We have shown in this paper that higher outcome uncertainty implies lower level of language complexity in the context of agent-based simulations of social interactions conceptualized as playing iterated Prisoner's Dilemma games. The complexity of the language was measured in terms of variability of the use of the language, and in particular in terms of variability of 'meanings' of lexical units of the language.

Considering that we modeled repeated social interactions through the iterated game playing, our result implies that in the case of social situations with high outcome uncertainty we expect a reduction in complexity of the language usage. More specifically, we expect a reduction in the range of possible/acceptable ways of usage ('meanings') of words, and possibly also an effective reduction of the size of the lexicon of used words. This matches well with the anecdotal evidence about very high outcome uncertainty environments like a surgical theatre or an army.

Data about variability of languages over larger geographical territories also suggests that our finding about the link between uncertainty induced by the environment and the (lexical) complexity of the language used by humans to live in these geographical areas is valid. Of course, this needs to be checked further and confirmed numerically on the basis of the data.

Our result indicates that environment induced uncertainty (represented as outcome uncertainty in our agent-based simulation study) plays an important role in the evolution of languages. This uncertainty implies complexity constraints on the language, which limit the lexical variability of the language. Such constraints may explain simplification of a language used in high uncertainty context and may also explain the variability of human languages in geographical areas characterized by high or low uncertainty implied by available resources (e.g. food, shelter, etc.).

Our analysis did not extend to cover the grammatical complexity of languages. This would need more complicated simulations allowing the change of the grammar (and symbol set of the lexicon) of the language used by agents. However, we conjecture that less lexical complexity may be compensated by more grammatical complexity in languages used in more uncertain environments.

Finally, our investigation of the link between outcome uncertainty and language complexity shows that the approach to measure language complexity as the average length of communication processes may not be sensitive enough to measure the effects of environment induced uncertainty. The proposed and used complexity measure which measures the variability of the usage of lexical elements is a more appropriate measure for this task, and possibly it is generally a more appropriate measure to measure lexical complexity of natural languages.

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