On Topic Selection Strategies in Multi-Agent Naming Game

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ABSTRACT

Communication is a key capability of autonomous agents in a multi-agent system to exchange information about their environment. It requires a naming convention that typically involves a set of predefined names for all objects in the environment, which the agents share and understand. However, when the agents are heterogeneous, highly distributed, and situated in an unknown environment, it is very unrealistic to assume that all the objects can be foreseen in advance, and therefore their names cannot be defined beforehand. In such a case, each individual agent needs to be able to introduce new names for the objects it encounters and align them with the naming convention used by the other agents. A language game is a prospective mechanism for the agents to learn and align the naming conventions between them. In this paper we extend the language game model by proposing novel strategies for selecting topics, i.e. attracting agent's attention to different objects during the learning process. Using a simulated multi-agent system we evaluate the process of name alignment in the case of the least restrictive type of language game, the naming game without feedback. Utilising proposed strategies we study the dynamic character of formation of coherent naming conventions and compare it with the behaviour of commonly used random selection strategy. The experimental results demonstrate that the new strategies improve the overall convergence of the alignment process, limit agent's overall demand on memory, and scale with the increasing number of the interacting agents.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Intelligent agents, Multiagent systems, Languages and structures

General Terms

Experimentation

Keywords

cognitive agent, language emergence, naming game

Cite as: On Topic Selection Strategies in Multi-Agent Naming Game, W. Lorkiewicz, R. Kowalczyk, R. Katarzyniak, B. Vo, *Proc. of 10th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2011)*, Tumer, Yolum, Sonenberg and Stone (eds.), May, 2–6, 2011, Taipei, Taiwan, pp. 499-506.

1. INTRODUCTION

Language is an extensively used everyday tool, as it allows individuals to gain, share and utilise information in a social setting. It is also a key capability of autonomous agents that facilitates the exchange of information and enables collaboration in a multi-agent system. As such, language constitutes the collective adaptation to the changing circumstances of the environment and advances the performance of certain social tasks.

Conveying information about the state of the environment, i.e. communication, requires that agents share a set of predefined names for all of the perceivable objects. However, it is very unrealistic to assume that all of the objects can be foreseen in advance, and that all of the required names can be defined and shared beforehand. Therefore, all agents need to develop from scratch, and further sustain, their individual names for all of the perceived objects.

In principle, word learning is a rather simple task of mapping linguistic labels onto a set of pre-established concepts [2]. However, the problem is far more complex in a multi-agent setting, as any differences in individual mappings, i.e. naming conventions, result in miscommunication between interacting agents. As such, agents not only need to develop and sustain their individual names, but most importantly need to align them to form a coherent shared naming convention. In particular, each autonomous agent, through a series of consecutive interactions with other agents, needs to align its private linguistic mappings. As such, a multi-agent system comprised of communicating individuals can be considered as a 'complex adaptive system' [17] that collectively solves the problem of developing a shared communication system.

Despite several studies [4, 14, 18, 21, 22] the problem of language alignment is still an active area of research [13, 18, 20]. Moreover, language game model [7, 8, 18, 19] defines a prospective mechanism for agents to learn and align their naming conventions. In this paper we introduce a novel approach of agent's attention orienting, i.e. topic selection strategies (see section 4) in language game, and evaluate its impact on the process of name alignment. Using a simulated multi-agent system, formalised in section 3, we study the dynamics of the language alignment process in the case of no feedback naming game[1]. Incorporating the adaptive cross-situational learning scheme [8], in section 5 we study the dynamics of the emergent process against different topic selection strategies that are utilised by the speakers. We show how a proper modification of the topic selection strategy may improve the overall convergence of the alignment process, limit the overall demand on memory, and scale properly with the increasing number of agents.

[1] No feedback naming game [19] is a type of language game [18] (see section 2)

Finally, in section 6, we analyse the mechanism underlining the observed behaviour and conclude the paper in section 7.

2. BACKGROUND AND RELATED WORK

The general problem of language alignment is fundamental to the field of multi-agent systems, especially embodied multi-agent systems. For instance, incorporating a flexible semantic communication system into a smart sensors network [5, 10, 23] may lower system's energy utilisation and extend its operation time. However, the most significant, and most appealing is the incorporation of language alignment mechanism in robotic systems [13, 16, 18].

To focus the attention, let us assume a group of spatially distributed mobile agents operating in an unknown, highly dynamic, spacious and possibly adversarial territory, similarity to settings proposed in [12] or [6]. All autonomous agents are embodied, situated (physically bounded) and distributed, all are capable of basic manoeuvring and all share a common task of monitoring the environment. Each individual is wandering around the environment collecting valuable information and occasionally engaging in interaction with the nearby agents. Depending on it's current intentions the character of such interaction may differ, from basic mutual identification, through information exchange, to a complex coordinated action. Nevertheless, vast majority of these interactions involve linguistic communication, where language facilitates the interplay between cognitive agents [3]. In order to convey information about objects from agent's sight, for instance to align the attention of interacting agents and focus on a particular object from the surroundings, agents must exchange meaningful symbols.

Obviously, in order to focus attention on the exact same object the population must share and utilise a certain naming convention, i.e. shared form of language[2]. A simple solution would involve an arbitrary label-object mappings that are predefined in the agents. However when the environment is unknown at the design time, a coherent naming convention cannot be build-in and shared by all the agents beforehand. Moreover, due to natural restrictions following from the embodiment, i.e. limited range, interface errors and costly long range communication, neither any explicit central coordination approach, nor any global communication scheme are suitable. Additionally, as each individual is an equally valuable source of information, a single 'leader' agent cannot be directly imposed on the system. Thus, agents are required to develop their naming convention from scratch, and are restricted to a local ad-hoc communication, i.e. linguistic interaction involving only the nearby members of the population and concerning only a relatively local set of encountered objects.

As the coherent naming convention cannot be build-in at the design time, each agent needs to be equipped with an internal mechanism of name acquisition. In principle, allowing the agent to introduce new names for unknown objects. However, due to distributed character of the population, there is a high chance that a certain object is labelled differently by multiple agents. As such, introducing competing labels and increasing the miscommunication between agents. In order to reduce the number of conflicting words, the agents should be capable of altering their label-object mappings and form coherent associations within the entire population. Unfortunately due to local ad-hoc communication restriction, each agent has only limited knowledge about the naming conventions utilised by others. In principle, only the occasional interactions between agents provide valuable insights on the general population naming stance. Nevertheless, as the available information is very narrow and highly limited, a simple approach towards alignment cannot guarantee that multiple agents will eventually agree on a shared object-label mappings. For instance, as an individual hearing a new word may presumably assign it to an infinite number of objects in its sight, leading to indeterminacy of meaning [15].

In fact, developing a mechanism that would lead to a coherent formulation of names among interacting individuals is not a trivial task [11]. Several approaches have been proposed and investigated in the literature [4, 22, 21, 18, 14], ranging from associative types of memory [18], through genetic algorithm models [21], to neural network adaptation [14]. The most promising approach addressing the aforementioned problem is the language game model (LGM) [18], where a population of agents thrives to develop a shared set of associations between signs and meanings, using communicative acts. LGM offers a general framework for modelling the possible emergence of language and formulates basic settings for linguistic interaction between agents. It assumes that each agent has its own, strictly private and individually emerged, word-object associations (names) that are stored in an associative type of internal memory - lexicon. In particular, as the lexicons are private, they may differ between agents resulting in naming conflicts that occur during interaction.

The idea behind the language game is that through a series of routine pair-wise interactions, the agents can align their lexicons reaching a coherent state of the entire population. In naming game, type of language game specified by LGM, a single interaction is described as a simple interplay between two agents, one acting as a speaker, and the other as a hearer. The speaker agent selects a single object from its sight and names it, according to its internal naming convention. Whilst the hearer uses the heard utterance as a clue to identify which of the objects was intended by the speaker. Depending on the feedback the agents receive after the game, and assuming that agents are equipped with a pre-developed pointing mechanism, three basic types of naming games can be identified [19]. In the simplest case, both agents receive feedback, as the hearer points to the intended interpretation, and as the speaker points to the intended topic. In the case of limited feedback, only the speaker receives feedback, as only the hearer points to the intended interpretation. In the no-feedback case, neither the speaker nor the hearer receive additional feedback after the game leaving both agents clueless about the results of their interaction. It should be noted that in the simplest case, the hearer is able to precisely deduct speaker's intended mapping between the name and the object. Whereas, the absence of pointing procedure significantly increases the hearers uncertainty, as all objects in its sight are equally probable topics, resulting in indeterminacy of meaning.

Basic properties of the alignment process were studied in most favourable types of environments and population settings, focussing mainly on the simplest (feedback based) case of Naming Game [18]. Using a straightforward cross-situational learning (CSL) mechanism embodied agents were able to learn the naming conventions based solely on co-variances that occur across different situations. In [19] it is shown that in a multiple objects setting the CSL is hard to properly scale-up with the increasing number of agents, and it is hard to reach proper coherence among the agents. As such, the early procedures were extended to incorporate additional mechanism of synonymy reduction [7] and homonymy damping [8] leading to a substantial improvement in their performance. The former, introduced additional notion of word utilisation, as a word score resembling the frequency of its successful usages, whilst the latter approach, introduced an adaptive alignment mechanisms, i.e. intelligent cross-situational learning (ICSL). In addition to regular enforcement and inhibition rules that steer the population of interacting agents to coherent word-meaning mappings, ICSL preserves the relative differences between concurring words that allow it to outperform other existing approaches in zero feedback naming

[2]Throughout this paper, language is perceived as a complex adaptive system [17] that can be represented as a weighted complete bipartite graph (See section 3)

game settings [8].

The extensive literature studies,including most recent summaries in [18, 20], show that despite its popularity the LGM has been investigated only in a limited set of basic settings[3], where uniform world structures, random attention orienting strategies, one-step pair-wise interaction pattern are assumed. As such in this paper we investigate the effect of introducing non classical attention orienting strategies, i.e. topic selection strategies in the LGM. We argue that a rational strategy should reflect agent's internal character and it's individual intentions, and not just uniformly sample agent's current sight, as in the existing formulations.

3. GENERAL MODEL

We introduce the formal model of the investigated case, and begin by formalising the state of the multi-agent system as a 4-tuple $\bar{S}(t)$, as follows

Definition 1. For each time point $t \in T = (t_1, ..., t_{K_T})$ a system state is a tuple:

$$\bar{S}(t) = \langle O(t), X_O(t), P(t), X_P(t) \rangle$$

- set of identifiable objects $O(t) = (o_1, ..., o_{K_O(t)})$
- context random process $X_O(t)$
- population $P(t) = (a_1, ..., a_{K_P(t)})$ of agents
- interaction random process $X_P(t)$.

The system state resembles a general state of the entire multi-agent system in a given point of time. It depicts currently identifiable objects O, currently operational agents P, and defines the externally imposed processes, i.e. the model of dynamic environment X_O (available through context) and the model of agent interaction X_P. As such, at each discrete time point t the random process X_O models the current state of the environment that is available to the system. Each agent $a \in P(t)$ perceives a certain part of its local environment - context $X_O^a(t)$ - as a set of objects in it's sight $\forall_{a \in P(t)}\ X_O^a(t) \subset O$. Analogous, the random process X_P for every time point t models the set of currently interacting agents, i.e. $X_P(t) \subset P^{K_I(t)}$, where $K_I(t)$ is the number of interacting agents.

In the assumed settings the context size is fixed $\forall_{t \in T, a \in P(t)}$ $\|X_O^a(t)\| = c$, and the interaction is limited to a single pair-wise $\forall_{t \in T} X_P(t) \in P(t) \times P(t)$ pattern. In the most general case, the set of identifiable objects and the set of all agents in the population can change during the system lifetime, however we assume a simpler case where both the set O and P are finite and static, i.e. $\forall_{t \in T} O(t) = O \wedge P(t) = P$.

3.1 Agent

An agent is the most fine-grained autonomous entity present in the system. It is embodied in the environment and is a part of the interacting population. In order to communicate, the agent needs to be equipped with an appropriate semantic infrastructure, that can be defined as the agent's state, as follows:

Definition 2. Agent's $a \in P(t)$ state in a given system state $\bar{S}(t) = \langle O(t), X_O(t), P(t), X_P(t) \rangle$ is a tuple:

$$\bar{A}(t) = \langle Ob^a(t), W^a(t), \mathcal{L}^a(t), \phi_P^a, \phi_I^a, \theta^a, \psi^a \rangle$$

- set of identified objects $Ob^a(t) = (o_1^a, ..., o_{K_{a,Ob}(t)}^a) \subseteq O$,
- set of words $W^a(t) = \{(w_1^a, s_1^a), ..., (w_{K_{a,W}(t)}^a, s_{K_{a,W}(t)}^a)\}$,
- lexicon mapping $\mathcal{L}^a(t) : W^a(t) \times Ob^a(t) \to [0, 1]$
- interpretation function $\phi_I^a(t) : W^a(t) \times \mathcal{L}^a(t) \to Ob^a(t)$,
- production function $\phi_P^a(t) : Ob^a(t) \times \mathcal{L}^a(t) \to W^a(t)$,
- topic selection function $\theta^a(t) : 2^{Ob^a(t)} \to Ob^a(t)$,
- update function $\psi^a(t) : W^a(t) \times 2^{Ob^a(t)} \times \mathcal{L}^a(t) \to \mathcal{L}^a(t)$.

Each object represents a self contained invariant in the external environment that is available to agent's perception and that encapsulates the smallest indivisible entity available to its higher processes. As the precise formulation of agent's perception is outside of the scope of this paper we assume that for each agent an object is explicitly identified by a unique and strictly internal identifier ($i \sim o_i^a$). Research in [8] assumed a static and fixed set of objects, we extend their settings allowing the agent to gradually build up the set of known objects Ob^a as it encounters them in the environment.

Words, on the other hand, are external representations identified by the population as dedicated communication signs. Each signal $w_j^a \in W^a$ is associated with agent's subjective notion of usability $s_j^a \in [0, 1]$ denoting its individual estimate of strength of a word spread in the population. The set of words that the individual uses is iteratively build up by the agent, as new words are invented by the speaker whenever it lacks a proper word for a given topic, and are incorporated by the hearer whenever it hears an unknown word.

In terms of linguistic capabilities the most important part of the agent is its lexicon, i.e. the mapping $\mathcal{L}^a$ that represents actual correlation $\sigma^a(o, w) \in [0, 1]$ between objects $o \in Ob^a$ and words $w = (w_i^a, s_i^a) \in W^a$. The higher it is the more definite the agent is that a certain word is an adequate name for an object. As such, the lexicon encapsulates the current state of agent's language, that for convenience can be viewed as a weighted complete bipartite graph $L^a = (V^a, E^a, \sigma^a)$, where $V^a = W^a \cup Ob^a$ is the set of vertices, $E^a = W^a \times Ob^a$ is the set of edges, and $\sigma^a(w, o)$ is the weight of an edge (w, o). Each agent is then able to interpret external utterance w_i^a, i.e. select the most adequate object o based on its current state $L^a(t)$, and produce the external utterance w_i^a, i.e. the most adequate name for a given object o based on its current lexicon state (see section 3.2). As such, the actual graph structure modulates agent's interpretation and production scheme. In particular, agent's two ϕ_P^a and ϕ_I^a schemes reflect certain method of traversing the lexicon graph, i.e. proper selection of the edges according to the current distribution of weights.

We further assume the well established mechanism of interpretation and production [8]. The interpretation scheme is rather straight forward, as for a given word $w = (w^a(t), s^a(t)) \in W^a(t)$ the interpretation function ϕ_I^a selects the edge $(w, o) \in E^a$ with the maximum weight ($\phi_I^a(w, L^a(t)) = argmax_{o_i} \sigma^a(o_i, w)$), and thus interprets w as referring to o. On the other hand, the production scheme assumes that the speaker before uttering a name evaluates its subjective reflection of the population, by considering the usability s of each possible word w. As such, for a given object o the production function ϕ_P^a selects the edge $(w, o) \in E^a$ with word w having the highest usability from all the words that the agent is able to interpret as referring to the object o ($\phi_P^a(o, L^a(t)) = argmax_{w_i}\{w_i : o = \phi_I^a(w_i, L^a(t))\}$), and thus names o.

3.2 Interaction

Interaction between agents is the only opportunity for an individual to verify the appropriateness of its language, and it is the only way to gain additional information about the naming conventions utilised by others. In the assumed settings, the interaction is governed by the means of no feedback naming game routine, where at each time point $t \in T$ a random pair of agents $X_P^a(t) = (a_S(t), a_H(t))$ where $a_S(t) \neq a_H(t)$ (a_S - speaker, a_H - hearer) advances in a simple communication. The speaker selects a single object $o_T(t)$ as the topic of conversation, according to its topic selection strategy $o_T(t) = \theta^{a_S}(X_O^{a_S}(t))$ and current context $o_T(t) \in X_O^{a_S}(t)$. Further, the speaker names the intended topic $w_T(t) = \phi_P^{a_S}(o_T(t), L^{a_S}(t))$, based on its current lexicon state

[3]For the sake of completeness, we note the research in [1], where different population structures were investigated in a minimal naming game (single object environment).

and utilising its production function $\phi_P^{a_S}$. Next, the uttered word is transmitted to the hearer, that receives it along with the current context of perception $X_O^{a_H}(t)$. It is assumed that the topic of the utterance is shared among both contexts, i.e. $o_T(t) \in X_O^{a_S}(t) \cap X_O^{a_H}(t)$. Based on this information, i.e. the context and the associated uttered word, the hearer updates its lexicon $L^{a_H}(t) = \psi^{a_H}(w_T(t), X_O^{a_H}(t), L^{a_H}(t-1))$, and interprets the utterance $o_I(t) = \phi^{a_H}(w_T(t), L^{a_H}(t))$[4]. As agents do not receive feedback concerning the outcomes of the game, the interpreted meaning and the heard word pair $(w_T(t), o_I(t))$ is regarded as the most probable one. As such agent's subjective notion of usability $s_T(t)$ of the heard word $w_T(t)$ should be increased, whilst the usability of all concurring names $\{w_i : o_I(t) = \phi_I^{a_H}(w_i, L^{a_H}(t))\}$, i.e. all other names that can be interpreted as the identified object $o_I(t)$, should be decreased. Moreover, learning from co-occurrence between words and objects (cross-situational learning) implies that after each interaction the hearer updates its lexicon $L^a(t)$ by modifying the correlations $\sigma^{a_H}(o, w_i)$.The update function ψ^{a_H} dampens the correlation $\sigma^{a_H}(o, w_i)$ between the received word w_i and currently not perceived objects $o \notin X_O^{a_H}(t)$, and enforces the correlation between the received word w_i and currently perceived objects $o \in X_O^{a_H}(t)$, while the correlations with other words remain unchanged. In settings involving context with multiple objects, a single interaction is typically insufficient to determine the utilised naming convention, as presumably all objects from the context are equally probable intended meanings. We note, that an object can dominate the correlation between a certain word only if it occurred, with this word, more times then with any other object.

3.3 Measures

In order to formulate differences in the dynamics of the alignment process, we identify two major axes of comparison, i.e. coherence and word statistics, and focus on the evolution of language in the assumed multi-agent system. We study the behaviour of the system based on four measures: success rate, language coherence rate, average number of used and overall number of words.

The most obvious measure is the frequency of successful communications between agents. It resembles the observed ability of the system to transfer information from one agent to another, and as such it allows to reason about the utility of the communication system itself. In order to keep track of the effectiveness of the communication we calculate the success rate μ_{SR}, as follows:[5]

$$\mu_{SR(N)} = \sum_{t \in T|_N} \mathcal{I}_{\{o_T(t) = \phi_I^{a_H}(\phi_P^{a_S}(o_T(t), L^{a_S}(t)), L^{a_H}(t))\}} \quad (1)$$

In general, the success rate $\mu_{SR(N)}$ of order N is the frequency of successful communications in the last N interactions $(T|_N)$, i.e. successful in terms of that both agents focus on the same object (1). In isolation, despite its simplicity, this measure is not very useful, as it does not take into account all objects from the environment, and can be easily deformed. For instance, agents communicating only about a single object are able to reach highest possible success rates, as they might share a common name for the preferred object, despite having poor coherence between other names.

Due to the above restrictions, we need to formulate additional measure resembling the naming convention spread among the entire population and reflecting the coherence of names among all existing objects. As such, we introduce language coherence μ_{LC}, as the probability that two randomly selected agents assign the same name for a randomly selected object from the environment, as follows:

$$\mu_{LC} = E_{a,a' \in P, a \neq a', o \in O}[\phi_I^a(\phi_P^{a'}(o, L^{a'}), L^a) = o] \quad (2)$$

The lowest possible coherence, i.e. $\mu_{LC} = 0$, reflects a state of no language coherence in the system, as there are no two agents that use the same name for any of the objects. The highest possible coherence, i.e. $\mu_{LC} = 1$, represents the state of full coherence, where all agents share the same naming conventions. It should be noted that in the assumed settings a system is absorbed by the coherent state, as from this point all of the utterances are consistent with the observed context, and without any external disturbance all of the strongest associations remain strongest.

In order to analyse the characteristics of the emergent language we keep track of the number of used words μ_{UW}, and keep track of the total number of all invented words μ_{TW}, defined as follows:

$$\mu_{UW} = E_{a \in P}[\|\{w \in W^a : \exists_{o \in Ob^a} \sigma^a(w, o) > 0\}\|] \quad (3)$$
$$\mu_{TW} = E_{a \in P}[\|W^a\|] \quad (4)$$

The former, is calculated as the average, over all agents, number of positively associated words, and it resembles the stability of current associations. As the optimal communication system has one-to-one mappings between words and objects, i.e. the same number of used words as the number of existing objects, and any deviation from this proportion reflects a potentially unstable situation, as miscommunication might occur. In the latter case, we calculate the overall number of existing words in the system, resembling again the stability of the communication system during its development. It should be stressed that new words may enter the lexicon, i.e. as agents are inventing new words, on regular basis. However, as it is not possible for a word w_j to leave the lexicon, the opposite mechanisms is a bit different, and a word can become disassociated through the dampening procedure, i.e. weight of associations $\sum_o \sigma(w_j, o)$ shared with w_j and/or usability s_j of w_j is close to 0. Nevertheless, the higher the number of different words in the system, the significantly higher is the number of all possible associations and possibly lower coherence. Moreover the higher the number of words, both used and invented, the more technically demanding the system is, as it needs more memory to store all associations and more processing power to cope with all possible association.

4. TOPIC SELECTION STRATEGIES

The most common strategy investigated in the literature is the purely random selection of topic, where a speaker uniformly samples its current context in order to select the intended meaning of its utterance. It is a rational approach in the presence of direct feedback, as the context degenerates into single object and different selection strategies do not affect the evolution of the system. However, in case of limited feedback and significant context sizes the topic selection strategy can significantly affect the overall evolution of the system (See section 5). We must underline the fact that, all of the following extensions relate only to the speaker. Moreover, as the hearer has no a priori knowledge about the strategy utilised by the speaker, we assume that it treats all utterances as a result of random sampling, and follows the behaviour described in section 3.

Different topic selection strategies can be analysed twofold, from the theoretical point of view and from a more pragmatic stance. The former approach assumes that selection is just a basic procedure of choosing a single object $o_T(t)$ from a set of objects $X_O(t)$. As such, the speaker agent a perceives current state of the environment as the context $X_O^a(t)$ of ongoing interaction, and in a predefined manner selects a single object $o_T(t)$ as the topic. From the more practical point of view, the topic selection strategy resembles the speaker's reaction to the recent state of the environment.

[4]If the intended meaning o_T is the same as the interpretation o_I then the game is considered successful, otherwise it is a failure.

[5]$\mathcal{I}$ is the identity function, i.e. $\mathcal{I}_{x=x} = 1$ and $\forall_{x \neq y} \mathcal{I}_{x=y} = 0$

As such, the context $X_O^a(t)$ is a form of short term memory that stores the most recent and most important objects, and depending on its internal perception the speaker agent a selects a single object $o_T(t)$ that it found valuable, interesting or significant. In this case topic selection strategy resembles the internal force that drives agent's attention, and orients its sensory receptors towards a particular object and away from other available stimuli [9]. Having this interpretation in mind, we formulate and introduce three basic topic selection strategies, and justify them as different points of attention that affect individual perception and cognition.

4.1 Random

As noted, the original model proposed in [8] assumes a purely random selection of topic, where at each time point the speaker is uniformly sampling its current context in order to select the topic of its utterance. In this case the topic selection function θ^{orig} (See equation 5) is a random variable with a uniform distribution over all objects in the context and can be defined as follows:

$$\forall t \in T\, Pr(\theta^{random}(X_O(t) = o)) = 1/\|X_O(t)\| \tag{5}$$

This situation resembles the case where the attention of the agent is randomly focusing on different objects in the environment. As such all objects are equally valuable to the agent, and uttering the name of each one of them is of an equal importance to the speaker.

4.2 Min / Max

It is obvious that perception is usually not passive, and it is the individual that is actively looking or listening in order to see or hear [9]. Previous strategy assumes no direct force that is applied on agent's perception, i.e. the agent perceives the environment in purely passive manner. However, agent's focus should depend on both, agents past observations and the current state of the environment. As such, attention of a curious agent should be attracted by a new, or relatively unknown objects from the environment. Resulting in agent's significant tendency to speak about the least occurring, in past interactions, object. On the other hand, attention of a more stagnant agent should be attracted by already familiar objects, or relatively known, objects from the environment. Resulting in agent's tendency to select the most occurring, in its past interactions, object. In principle, both, i.e. min and max, approaches represent two similar forces that drive the attention of an individual. One is focusing on the least known elements of the environment (min), whilst the other on the most known elements of the environment (max).

We further assume that each agent $a \in P$ is able to store the frequencies $F^a(t) = \{f_1^a(t), ..., f_{K_{a,Ob}}^a(t)\}$ of the observed occurrences of the encountered objects in its past interactions. This basic statistics is further stored as agent's private knowledge about the environment, and is utilised in its future interactions to drive agents attention towards certain aspects of the environment. In this case the topic selection functions θ^{min} and θ^{max} are deterministic functions that for a given state of the environment select the most and least frequent object, respectively. In order to maintain the probabilistic notation we denote this deterministic functions as a random variable with a Dirac delta distribution as follows:

$$\forall t \in T\, Pr(\theta^{\max}(X_O(t) = o_i) = \begin{cases} 1, & f_i = \max_j f_j \\ 0, & \text{otherwise} \end{cases}$$
$$\forall t \in T\, Pr(\theta^{\min}(X_O(t) = o_i) = \begin{cases} 1, & f_i = \min_j f_j \\ 0, & \text{otherwise} \end{cases}$$

4.3 Preference

The point of attention of the system can also depend entirely on the internal structure of the agent, i.e. as the agent may have certain preferences over the objects, or as simply its perception may be attracted by certain objects. As such it is the embodied, i.e. physical properties of the perception apparatus, and the internal structure, i.e. pre-build preferences and biases, that has significant impact on agents orientation. For instance, being equipped with very sensitive microwave sensor the agent might have tendency to focus on objects that emit such wavelengths, and as such naturally tend to select them as the intended topics.

In this paper we assume that each agent has a predefined set of preferences $R^a(t) = \{r_i^a(t) : o_i \in Ob^a(t)\}$ over the objects. These preference values r can be understood as affordances, i.e. individual utility of an object as perceived by the agent. Without any loss of generality preferences can be treated as probabilities, where for every agent $a \in P$ following conditions hold $\sum_{r \in R} r = 1$ and $\forall_{r \in R} r \geq 0$. In such a case we can model the topic selection functions θ^{pref} (See equation 6) as a random variable with a discrete distribution over the objects defined by the preferences structure $R^a(t)$ as follows:

$$\forall t \in T\, Pr(\theta^{pref}(X_O(t) = o_i)) = r_i(t) \tag{6}$$

5. EVALUATION

In order to evaluate different topic selection strategies we perform numerous simulations. All experiments share a common framework, and assume finite, static set of objects O and agents P, all incorporate a uniform interaction process[6] with a pair-wise communication model ($a_S(t) \neq a_H(t)$), and all are restricted to a shared context setting ($o_T(t) \in X_O^{a_S}(t) \cap X_O^{a_H}(t)$). Moreover, it is assumed that agent's behaviour is governed by a set of standard interpretation ϕ_I, production ϕ_P, and update ψ rules, as described in section 3. We investigate a number of simulation settings, including various population sizes, various object sizes and different context sizes using versatile measures, from basic success rate, to more complex synonymy and homonymy spread in the population. However, due to the space limitations we only focus on the general properties of the system, and present the obtained results as an exemplification of the observed system's behaviour.

Baseline parameters assume: ten agents, ten objects, fixed context size limited to two objects, and random selection strategy. All of the presented graphs are an average over fifty consecutive runs and as such are a good representation of the observed dynamic behaviour of the system. In order to compare the topic selection strategies it is important to guarantee the same experimental settings for each selection procedure by fixing the context path (sequence of randomly generated consecutive context) and interaction path (sequence of randomly generated consecutive agent pairs) before each run, and sharing it with all of the strategies.

5.1 Success rate and language coherence

Figure 1 depicts the typical character of language coherence dynamics. On the right column graphs, we can observe the slow phase shift dynamics of the coherence rate (See equation 2), reflecting three fundamental stages of system's evolution. Whilst, on the left column, we can observe the typical dynamics of the success rate (see equation 1).

Initial iterations form and maintain a plateau of low coherence, where the early invented words shape hooks that gradually begin to fill up agent's lexicons with words and cast fresh possible conventions (see section 5.2). Despite, the initial burst of new conventions and sudden increase of the overall usability of words s_i, the average strength of correlation σ is still relatively low. In the second phase the system undergoes a sudden increase of coherence. Due to a particular realisation of random processes X_O and X_P, some

[6] where each pair of agents is equally probable to interact

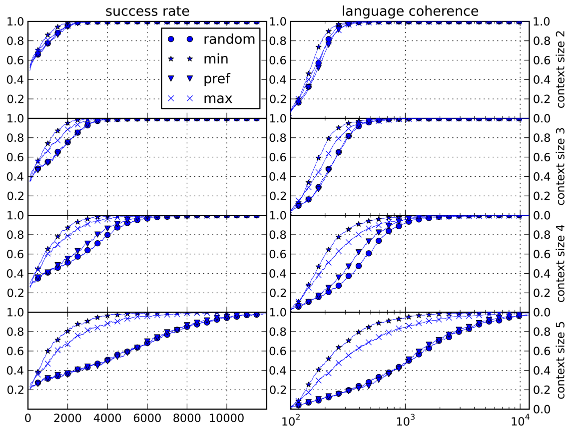

Figure 1: **Success rate and language coherence in different topic selection strategies and four different context sizes.**

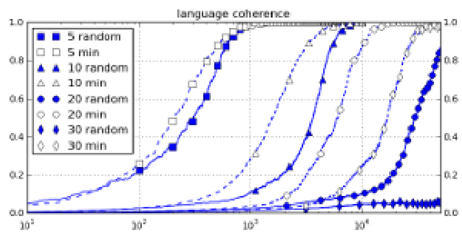

Figure 2: **Language coherence in different topic selection strategies and three different population sizes (context size set to 4).**

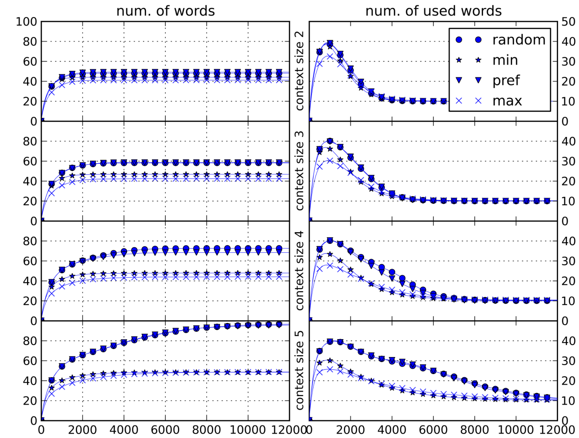

Figure 3: **Number of words and used words in different topic selection strategies and four different context sizes.**

of the initial hooks are dampened, as such some of the words are no longer used (see figure 3), whilst the other ones are enforced, as such the overall strength of correlation of the used words increases. Resultant, the strongest words start to dominate the convention and can be easier shared among the individuals. The last stage resembles the significant slow down in alignment process. As most of the language is already shared by the agents, i.e. the coherence level is above $\mu_{LC} = 0.8$ (80% of the maximum coherence), and due to the random character of participant and context selection, the less probable, and still unaligned, cases must occur, i.e. the minority must adopt the dominant naming convention.

Three basic observations can be made from the obtained results (see section 6). At first higher levels of coherence are reached by the min(max) strategy, i.e. at each iteration it is higher compared to random strategy. Secondly, the more significant the context size is, the more significant is the observed disproportion. As observed in figure 2 analogous tendency is maintained with the increase of population size. Third, the min/max strategies seem to resemble very similar characteristics under the influence of changing context size.

5.2 Words statistics

Figure 3 depicts the typical dynamic character of the average number of words used by an individual (see equation 3) and the overall number of words present in the system (see equation 4). As already noted the system undergoes three distinguishable phases. Initially, as agents lexicons begun to fill up with words, and as agents still lack of precise information, a sudden increase in the number of used words is observed. Reaching its maximum at about the level of 20% of the maximum coherence (see section 5.1). Further, as some of the initial formed names, due to random character of the process, are more 'popular' they tend to dominate the population, and begin to systematically eliminate all other competing words from their usage. This early alignment results in the observed sudden decrease in the number of used words, and is correlated with the increase of language coherence (see section 5.1). In short, as agents begin to share more and more conventions, all of the most obviously incorrect ones, least 'popular', can be quickly dampen. Obviously, this decrease is less sudden then the initial burst, and it steadily diminishes with time. Again, the last stage resembles the significant slow down in the alignment process, as the minority must aligned to the dominant convention. Finally, the number of used words stabilises at the number of objects present in the environment, reaching as such the ideal one-to-one naming convention (see section 3.3).

Again three basic observations can be made from the obtained results. At first, the maximum number of words directly depends on the number of objects in the context and on the selection strategy. In case of random selection the increase of needed number of words, with the increase of context size, is significant, whereas the min/max strategies are more or less stable. Importantly, the min (max) strategy in all context sizes requires significantly less words, also less used words, then the random strategy. Secondly the more significant the context size is the less words are needed for the min/max strategies, and the more significant is the disproportion between min (max) strategy and the 'other' strategies. Third, the min/max strategies seem to resemble very consistent characteristics without any significant influence from the changing context size. The number of invented words is stable at around the same level (40) for both strategies, and for both strategies the maximum number of used words undergoes similar change, i.e. decreases with the increase of context size.

5.3 Dynamic context size

In all of the previous simulations a fixed context size settings were assumed, where $\forall_{t \in T} \|X_O(t)\| = c$. However, despite its analytical simplification it is still a significant limitation imposed on the system, as it requires that all interactions between agents involve a strictly predefined number of objects from the environment - $c \leq K_O$. Therefore, it is reasonable to ask how general is the observed behaviour, and whether it is not only restricted to a fixed context settings. In order to verify this notion, we introduce a modification to the previous settings and before interaction alter the number of objects present in the context. Introduced change is governed by a predefined probability distribution, i.e. $Pr(X_O(t) = c)$. In particular, as all objects are equally probable to appear in the

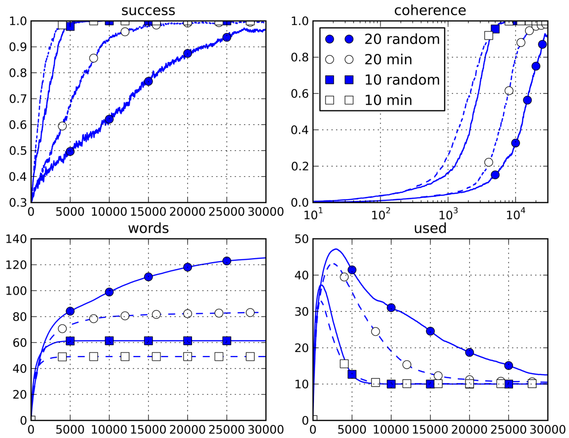

Figure 4: Varying context size settings.

context it seems rational to investigate an analogous type of distribution, where $Pr(X_O(t) = c) = \frac{1}{K_O}$. We should note that on average, as the number of interaction increases, each agent interacts equally often in each possible context size setting, e.g. equally often perceives a single object ($c = 1$), and equally often perceive the entire set of objects ($c = K_O$).

Figure 4 represents a typical behaviour of the alignment procedure in dynamic context settings. As in fixed context settings the min/max strategies result in higher coherence rates, however due to the aforementioned independent cases and the dynamic character of their change the increase is less significant. Nevertheless, still the min/max selection strategies require less words to reach a coherent naming convention, as such limit the required memory of the system and limit the number of used words in the system. Additionally, dynamic context sizes still maintain the scaling property, as with the increasing number of objects the difference between language coherence of random and modified selection is increasing. In short, it should be noted that the behaviour pattern of the alignment process in case of dynamic context sizes remains consistent with the observations for the case of fixed context structures.

6. ANALYSIS

We can recall that the considered learning mechanism is based solely on learning from co-occurrences between words and objects (cross-situational learning), and the more agents 'talk' about a certain object the more names are invented and more conventions tested. Moreover, the more different agents start to talk about the same set of objects the more possible naming conflicts might occur, i.e. more conflicts must be resolved and the names must concur with other numerous competitors.

At first, the noticeable differences between the random and min (max) strategy may be falsely attributed to the specificity of the assumed experimental settings. Seemingly, the limited number of agents increases the probability that multiple agents share similar statistics of the environment, i.e. similar private frequencies $F(t)$. As such, whenever speaker selects the least (or the most) occurring object the shared frequencies increases the chance that the hearer also perceives the topic as rare, and resultantly both agents tend to select similar objects. In particular, being in line with hypothetical specificity of the assumed settings requires that with the increasing number of agents the disproportion between min/max and random strategy should diminish. As this behaviour is not observed, i.e. the results presented in figure 2, it supports our justification that the presupposed similarity of perceptions between communicating individuals does not influence the tendency to dominate correlations.

The key to understand the significant difference between the random strategy and min/max strategies lies in the characteristics of the random process that each selection strategy represents. The fundamental probability that a given object o is present in the context is given as $p_o = Pr(o \in X_O(t)) = \frac{1}{K_O}$, and therefore the probability that a certain frequency increases is $Pr(f_i(t_2) > f_i(t_1)) = p_{o_i}$ (t_1 and t_2 indicate two consecutive time points when the agent interacted). Fixing a strategy, results in speaker's linguistic behaviour being governed by its selection θ process, that in case of min/max strategy is additionally modulated by the perceived statistics of the environment.

Let us consider an isolated (single speaker agent) process of random topic selection, at each time point a given number of objects c is drawn (without replacement) from a set containing K_O identifiable objects and put into a shared bin B, i.e. $Pr(o_i \in B) = \binom{K_O-1}{c-1} \cdot \binom{K_O}{c}^{-1} = \frac{c}{K_O}$. Further, a random object $i*$ is selected from the bin, i.e. $Pr(o_{i*} = \theta^{orig} | o_{i*} \in B) = \frac{1}{c}$. The resultant probability of object o_{i*} being selected is equal to $Pr(o_{i*} = \theta^{orig}) = Pr(o_{i*} = \theta^{orig} | o_{i*} \in B) \cdot Pr(o_{i*} \in B) = \frac{c}{K_O} \cdot \frac{1}{c} = \frac{1}{K_O}$. If the latter selection procedure is uniform, representing the random strategy, the initial distribution of objects is maintained, i.e. each object is equally probable to be selected as the topic. Based on this observation the expected number of times an object o was selected by the speaker $X_o^{a_S}(N)$ after N iterations is equal to $E[X_o^{a_S}] = N \cdot Pr(o = \theta^{orig})$, as the process X^{a_S} follows the multinomial distribution. As such, all objects are evenly selected by all agents, and significant number of naming conflicts occurs. This is in line with simulation results (See figure 2), where in early stage the number of concurring words increases drastically and the number of invented words is significant.

On the other hand in the case of min/max selection strategy the presented procedure must be extended to a case where for every drawn object o_i an identical one is added to a shared bin, whilst the original one is returned to the set. As such the number n_i of objects of type i in the shared bin constitutes the frequency of a certain object $f_i = n_i / \sum_j n_j$. Now if at each iteration the agent selects the bin with lowest / highest number of balls, then this process represents min / max strategy appropriately. Let us assume a simple case, where there are only two objects o_1 and o_2 present in the environment. At each iteration a single agent $a \in P$ along with one object o_i is randomly selected, increasing agent's a frequency of o_i occurrence f_i^a. Afterwards agent a selects a single object (o_1 or o_2) based on its current frequencies (f_1^a, f_2^a) and (min/max) strategy. After N iterations the probability that the frequency of occurrences is equal for both objects is $Pr(f_1^a(N) = f_2^a(N)) = \frac{1}{2}^N$, and it significantly decreases with the number of iterations. As $\theta^{min} = argmin_{o_j} f_j^a$ the probability that after N iterations the selection process is going to switch objects is equal to $Pr(f_1^a(N) = f_2^a(N)) Pr(\theta^{min}(N-1) \neq \theta^{min}(N+1)) = \frac{1}{2}^N \frac{1}{2}$. Obviously, with the increasing number of iterations the probability that the agent a used to select $o_1(o_2)$ will switch to $o_2(o_1)$ is decreasing exponentially, e.g. for $N = 10$ the probability of switching is .05‰, and is highly defined by the early realisation of the random selection. Resultantly, the agent has a strong preference over one of the objects (opposite to random selection). It should be noted that as agents do not share their private perceptions the frequencies differ between the individuals, and result in even distribution of preferences between agents, i.e. most likely the same number of agents will prefer o_1 as o_2. As such in case of min/max strategy, the population of interacting agents randomly transforms themselves into a population of individuals that tend to speak about different parts of the environment, i.e. individuals that tend to have unique selection preferences. Whilst in the case of random strategy, the population of interacting agents resembles an opposite transformation into a group of individuals that tend to equally (in terms of frequency) speak about all parts of the environment. As such in case of min/max approach the agents need to invent less words (see section 5.2), i.e. on average less conflicts occur, and due to limited possibilities the higher coherence is easier to achieve (see section 5.1). Interestingly, as the context size increases the agent's preferences, selection strategy, tends to be more specialised and focusing on a single object. Therefore the observed decrease in number of needed words in increasing context sizes (see figure 3).

7. CONCLUSIONS

In principle, developing a mechanism that would lead to a coherent formulation of names among multiple interacting individuals is not a trivial task. Several approaches have been proposed and investigated in the literature, however, the language game model seems to be still the most significant framework for language emergence. Presented approach is in line with the ongoing research, as it extends the 'classical' LGM approach of random topic selection, and studies the dynamic character of the formation of coherent naming conventions. Using a simulated multi-agent system we give insights on the effects of different attention attracting procedures, i.e. topic selection strategies, in the case of the least restrictive type of naming game (without feedback).

The attention orienting strategies are an important aspect in the research on language emergence based on the language game model. In this paper we have introduced three general meta-models of different topic selection mechanisms, and studied their effects on the behaviour of no feedback naming game with significant contexts sizes. We justify that incorporation of different topic selection strategies influences the behaviour of the system, resulting in higher levels of language coherence and maintaining a the minimal memory requirements. Moreover, we show that the more significant the context size is the more significant is the observed disproportion between different strategies. In particular, we have shown that the 'classical' settings of random selection do not guarantee the best performance, and can be easily enriched through a more deterministic strategy. Higher levels of coherence can be reached by agents tending to select the best known objects (max strategy) or tending to select the least known objects (min strategy). Additionally, the more the agents in the population then again more significant is the observed disproportion between different strategies. As such, we show that min/max topic selection strategies scale significantly better then the extensively used random selection.

Our future research focuses on extending the proposed mechanism to a more flexible population structures and less restrictive environments. We further intend to introduce adaptation procedures that would allow to dynamically modulate agent's selection strategy, allowing to study more advanced and complex models of attention orienting.

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