Active Control of Complexity Growth in Naming Games: Hearer's Choice

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How do linguistic conventions emerge among a population of individuals? A shared lexicon can self-organize at population level through local interactions between individuals, what has been shown in the Naming Games computational framework. However, the dynamics of the convergence towards this shared convention can differ a lot, depending on the interaction scenario. Infants, who acquire social conventions really fast, control actively the complexity of what they learn, following a developmental pathway. Adults also adapt the complexity of their linguistic input when speaking to language beginners. We show here that such active learning mechanism can improve considerably the speed of language formation in Naming Game models. We compare two scenarios for the interactions: either the speaker exherts an active control, or the hearer does. The latter scenario shows faster dynamics, with more robustness.

1. Motivations

How does language emerge, evolve and gets transmitted between individuals? What mechanisms underly the formation and evolution of linguistic conventions, and what are their dynamics? Computational linguistic studies showed that local interactions in groups of individuals (e.g. humans or robots) can lead to self-organization of lexica associating semantic categories to words (Steels, Kaplan, McIntyre, & Van Looveren, 2002). However, it still doesn't scale well to complex meaning spaces and a large number of possible word-meaning associations, implying high competition among lexical conventions.

In statistical machine learning and in developmental sciences, it has been argued that an active control of the complexity of learning situations can have a significant impact on the global dynamics of the learning process (Gottlieb, Oudeyer, Lopes, & Baranes, 2013; Lopes & Montesano, 2014; Kaplan, Oudeyer, & Bergen, 2008). This approach has been studied mostly for single robotic agents learning sensori-motor affordances (Oudeyer, Kaplan, & Hafner, 2007; Moulin-Frier & Oudeyer, 2013), but active learning might represent an evolutionary advantage for language formation at the population level as well (Oudeyer & Smith, 2014; Steels, 2004).

Naming Games are a computational framework, elaborated to simulate the self-organization of lexical conventions in the form of a multi-agent model (Steels, 2001). Through repeated local interactions between random couples of agents (designated *speaker* and *hearer*), shared conventions emerge. Interactions consist of uttering a word - or an abstract signal - refering to a topic, and evaluating communication success or failure.

However, a lot of processes involved in these interactions are random choices, especially the choice of a communication topic. Some preliminary work on the introduction of active learning algorithms in these models already shows significant improvement of the convergence process towards a shared vocabulary, but only with the speaker actively controlling vocabulary growth (Oudeyer & Delaunay, 2008; Schueller & Oudeyer, 2015; Cornudella, Van Eecke, & Van Trijp, 2015) .

Memorization skills of infants are improved through active query of lexical knowledge (Partridge, McGovern, Yung, & Kidd, 2015), and experiments with children learning tasks in a social context suggest that this active behavior may also be part of the mechanisms used naturally in an interacting population of human learners (Vredenburgh & Kushnir, 2015). In this work, we adapt the existing algorithms to a variant of the Naming Games where the hearer is actively controlling the complexity growth of the shared lexicon.

2. Methods

2.1. *Interactions*

The exact interaction process used in this work can be described as follows: Among the population, two agents are randomly picked and designated as speaker and hearer. A topic is chosen within the set of possible meanings (either randomly or actively by one of the agents), and the speaker utters the word associated (in its own vocabulary) to this meaning. The hearer then guesses the meaning of the word, and compares it to the actual topic. If the two meanings match, the interaction is successful. Otherwise, the communication is a failure, and both agents have the opportunity to update their vocabularies. We distinguish here three different scenarios: the topic is chosen randomly (like in the original models), either by the speaker, or the hearer (figure 1).

Vocabularies are represented as binary matrices, rows and columns being respectively meanings and words. The sets of meanings $\mathcal{M}$ and words $\mathcal{W}$ are finite (cardinalities M and W) and symbolic (no grounded meaning or word). All N agents of the considered population start with empty vocabularies (all-0 matrices).

In Wellens (2012), a classification of Naming Games interaction types is proposed. We will employ one of the vocabulary update method described there, the *Imitation Strategy* (figure 2, choice explained in section 4). An agent always adds to its vocabulary the meaning-word association used in the interaction, erasing all potential synonyms or homonyms. This ensures a maximum of one associated word per meaning.

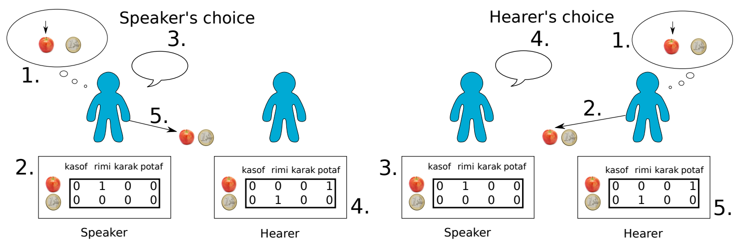

Figure 1. Interaction process for both active scenarios considered in this work. Beforehand, two individuals have been randomly selected among a population, an designated as speaker (S) and hearer (H). Speaker's choice: 1. S chooses a topic, 2. S checks its vocabulary to find or invent an associated word, 3. S utters the word, 4. H guesses the intended meaning, 5. S indicates the intended meaning. Hearer's choice: 1. H chooses a topic, 2. H indicates the intended meaning, 3. S checks its vocabulary to find or invent an associated word, 4. S utters the word, 5. H checks its vocabulary for a meaning associated to the uttered word. In both cases, if all meanings match, the interaction is considered a success, otherwise a failure. After the process, both agents can update their vocabularies.

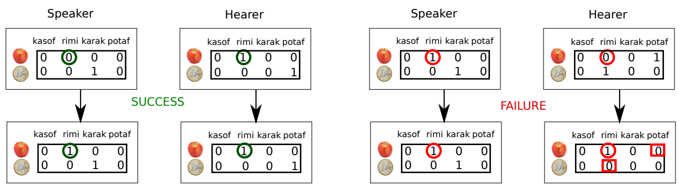

Figure 2. Vocabulary update policy: in the two interactions described here, topic was the object apple, and uttered word was *rimi*. When the speaker is refering to an unlabeled (for him) meaning, it creates an association during the update. When an interaction fails, the hearer adds the used association, and erases any conflicting homonym or synonym.

2.2. *Strategies for the active choice of topics*

During an interaction (figure 1), one of the involved agents (speaker or hearer) chooses the topic, i.e. the meaning infered by the speaker. This choice is done with only local information; in other words an agent doesn't access the memory of the others. The way of picking of the topic is called a strategy. A uniform random choice over the set of meanings is called the naive strategy.

The three active strategies used in this work (figure 3) cover a certain diversity of active mechanisms. This work analyzed 3 different strategies, each of which balances two types of behaviors: choosing an unlabeled meaning (to increase the vocabulary size) or choosing an already labeled one (in order to consolidate the existing vocabulary). In the latter case, the agent employs a confidence function to discriminate among known meanings those which would benefit consolidation in priority.

Naive (random)	Success Threshold	Minimal counts	Info. Gain softmax
$m \leftarrow$random($\mathcal{M}$)	**if** mean$\left(\frac{succ(i)}{succ(i)+fail(i)}\right)_{i\in\mathcal{LM}} \geq \boldsymbol{\alpha}$: $m \leftarrow$random($\mathcal{UM}$) **else**: $m \leftarrow$argmin$_{i\in\mathcal{LM}}\left(\frac{succ(i)}{succ(i)+fail(i)}\right)$	**if** $\forall i \in \mathcal{LM}\ succ(i) > \boldsymbol{n}$: $m \leftarrow$random($\mathcal{UM}$) **else**: $m \leftarrow$argmin$_{i\in\mathcal{LM}}(succ(i))$	**if** $P_{exp}(\mu,\boldsymbol{\beta}) \geq$ random($[0,1]$): $m \leftarrow$random($\mathcal{UM}$) **else**: $m \leftarrow$random($\mathcal{LM}$)
$\mathcal{M}$: all meanings, $\mathcal{LM}$: labeled meanings, $\mathcal{UM}$: unlabeled meanings, μ: vocabulary size (# word-meaning associations) $succ$: # successful interactions per meaning, $fail$: # failed interactions per meaning, P_{exp}: equations 1, 2 and tabular 4			

Figure 3. Strategies: Choice of meaning m (by speaker or hearer, depending on the scenario)

Speaker:

$$P_{exp}(\mu,\beta) = \frac{e^{\frac{G(+1)\cdot p(+1)}{\beta}}}{e^{\frac{G(+1)\cdot p(+1)}{\beta}} + e^{\frac{G(-1)\cdot p(-1)}{\beta}}} \quad (1)$$

Hearer:

$$P_{exp}(\mu,\beta) = \frac{e^{-\frac{G(-1)\cdot p(-1)}{\beta}}}{e^{\frac{G(+1)\cdot p(+1)}{\beta}} + e^{-\frac{G(-1)\cdot p(-1)}{\beta}}} \quad (2)$$

Speaker's choice		
$\Delta\mu$	Info. Gain G_μ (bits)	Probability p_μ
$+1$	$\log_2(W-\mu)$	$\frac{(M-\mu)(W-\mu)}{MW}$
0	0	$\frac{\mu(1+M+W-2\mu)}{MW}$
-1	$-\log_2(W-\mu+1)$	$\frac{\mu^2-\mu}{MW}$

Hearer's choice		
$\Delta\mu$	Info. Gain G_μ (bits)	Probability p_μ
$+1$ (explore)	$\log_2(W-\mu)$	$\frac{W-\mu}{W}$
0 (explore)	0	$\frac{\mu}{W}$
0 (check)	0	$\frac{W-\mu+1}{W}$
-1 (check)	$-\log_2(W-\mu+1)$	$\frac{\mu-1}{W}$

Figure 4. In both studied scenarios, hearer's possible outcomes with associated gains and probabilities, when having μ associations in the vocabulary $\mathcal{V}$. There are M meanings and W words. To determine the probabilities, each agent assumes the other agent's vocabulary to be a permutation of its own or in other words, that they share the same μ value. Information measure (defining the gain) is introduced in section 2.3.

2.2.1. *Success threshold*

The Success Threshold strategy was first introduced in Oudeyer and Delaunay (2008). The confidence function is the percentage of successful interactions, computed for each meaning. If its average value exceeds a given threshold (parameter α), the agent will choose an unlabeled meaning. Otherwise, the meaning with the lowest confidence value is chosen (randomly in the original definition).

2.2.2. *Minimal count of successes*

This strategy is defined by a confidence function being the sum of successful interactions, per meaning. If it is higher than a given minimum value (parameter n) for all labeled meanings, the agent will choose an unlabeled meaning. Otherwise, the meaning with the lowest value is chosen.

2.2.3. *Information gain soft maximization*

This strategy is an extension of the Information Gain maximization strategy introduced in Schueller and Oudeyer (2015). The agent chooses between exploring or teaching/checking depending on the expected outcome of the interaction in each case, always for the hearer, quantified as information gain (see 2.3). The choice is done according to a soft-maximization probability distribution (parameter β). Those expected values are computed following a simple assumption: the other agent involved in the interaction has a vocabulary of the same size, but completely independant. In other words, it is supposed to be a random permutation of the binary matrix representing the vocabulary of the decision-making agent. A speaker, if making a decision, will prefer to maximize its outcome for each given hearer. A hearer on the other hand will prefer to check, while minimizing the information loss and avoiding early exploration (see equations 1 & 2).

2.3. *Measure*

To compare the strategies, we will use the measure introduced in Schueller and Oudeyer (2015). It describes convergence towards a state where all agents have an identical vocabulary, hence sharing a common lexicon. Computed over a population of agents, it takes values in range $[0, 1]$. When the measure equals 0, no agent shares any word-meaning association with any other (maximum distance to converged state), whereas a value of 1 means the population has converged. The exact definition of the measure is the normalized quantity of shared information between 2 agents' vocabularies, averaged over all possible couples in the population. All strategies used, including the naive one, do converge in finite time. The only constraint is M$\leq$W. A proof can be found in Schueller and Oudeyer (2015).

3. Results

3.1. *Parameters*

To set the parameter of the strategies, we will use the method introduced in Schueller and Oudeyer (2015) and retain values yielding fast convergence dynamics. We ran simulations for different values of the parameter spanning the possible interval, and plotted a snapshot of the status of all simulations after a given number of interactions. We then inferred a best value for the parameter, while having an idea of the robustness of this choice. In all the simulations of this paper, we used M=W=N=20.

In all cases we found parameter values yielding convergence in less than 10.000 interactions. According to figure 5, for speaker's choice: $\alpha = 85\%$, $n = 20$ and $\beta = 0.2$; for hearer's choice: $\alpha = 85\%$, $n = 0$ and $\beta = 0.35$. The flatness of the curves indicates that hearer's choice parameters are more robust to a change in value than in the speaker's choice scenario.

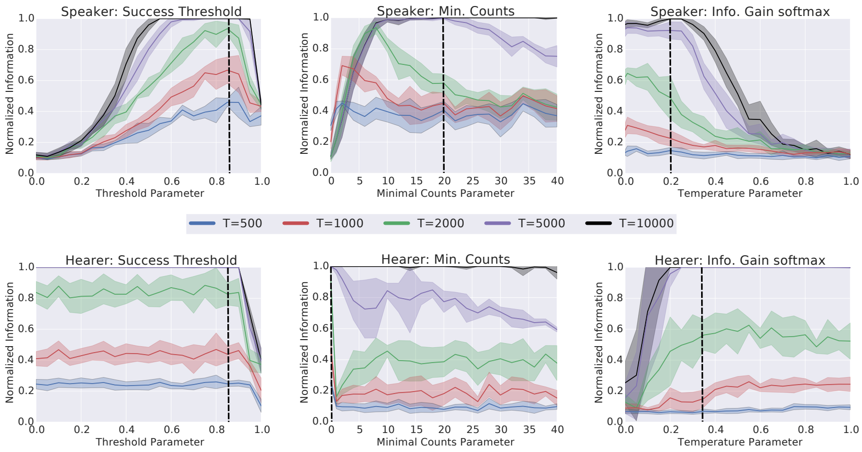

Figure 5. Convergence speed dependance on strategy parameters, for 3 strategies and 2 active interaction scenarios (see section 3.1, strategies described in section 2.2). In all cases hearer's choice scenario parameters are more robust to change in value. Snapshots are taken for concurrent strategies spanning a relevant parameter interval, at different time steps (500, 1000, 2000, 5000, 10.000 interactions). Vertical lines show parameter values chosen for the comparisons in figure 6. (M=W=N=20, averaged over 8 trials)

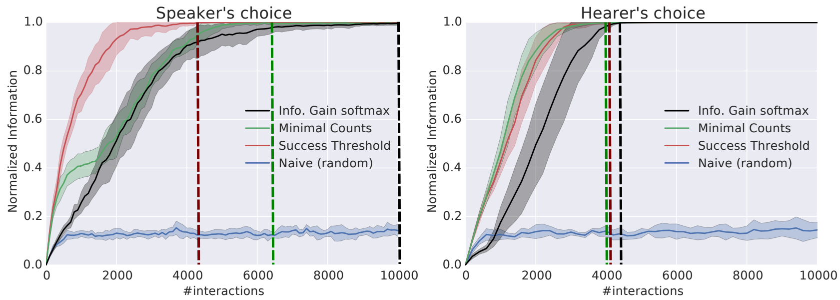

Figure 6. Strategy comparisons in both active scenarios. Naive strategy converges slowly (after 1.000.000 interactions – not depicted here). Hearer's choice policy is more efficient for all active learning strategies. Last 5% of information are acquired slower when the speaker is choosing. Vertical lines show full convergence time for each strategy. (M=W=N=20, averaged over 8 trials)

3.2. *Comparison*

As we can see in figure 6, active learning strategies were shown to speed up convergence significantly, for all tested strategies. Convergence to a shared lexicon over the whole population was reached between 4000 and 10.000 interactions, which was a significant improvement compared to the naive strategy (converging after 10^6 interactions).

In the hearer's choice scenario, convergence process is faster for all active learning strategies. However the success threshold strategy shows similar dynamics in both scenarios for the first 95% of normalized information. The last 5%, for all strategies, are slowly acquired when the speaker is choosing, compared to the dynamics of the first 95%. When the hearer is choosing, the dynamics of the last 5% stays comparable to the overall dynamics. Information gain maximization is slower than the other two strategies. Minimal counts strategy shows a shift in convergence speed when speaker is choosing and the set count value is reached. When the hearer is choosing, it performs as well as the success threshold strategy.

4. Discussion

It is important to understand that our research was carried out with the assumption of Imitation Strategy. Other possible vocabulary update policies, including "Minimal" and "Lateral Inhibition" (see Wellens (2012)), are likely to exhibit different convergence rates. The information measure from Schueller and Oudeyer (2015) is not yet defined for those cases, but an extension of the study including those alternative vocabulary update policies is planned.

In this work, we have shown that active information request by the hearer can be a more efficient policy than active information provision by the speaker, in the Naming Games framework. The observed difference between the two policies lies mostly in the acquisition dynamics of the last 5% of information. These findings support that high correlation between vocabularies is best handled by active learning than by active teaching.

Furthermore, active information request is more robust, as a wide range of parameters lead to improved dynamics (compared to random choice), for all studied algorithms. On the other hand, the parameters need to be finely tuned for the speaker's choice policy. This could be understood as a difference in required skill-level between policies. From an evolutionary point of view, it implies that an active information request behavior may be developped faster.

If the dependance of the results on the numbers of meanings, words and agents first needs to be studied, the next logical step would be to mix both policies, by giving agents the opportunity to take turns. Deciding speakers may bring faster dynamics at the beginning, and hearers near the end of the lexicon establishment process. An active choice of the partner, like humans selecting who they may prefer interacting with, could also bring some further improvement.

Source code

The code used for the simulations of this paper was written in Python. It is available as open source software, along with explanatory notebooks, on the Inria Flowers team github: **https://github.com/flowersteam/naminggamesal**

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