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Extended Abstract

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ABSTRACT

This paper introduces a methodology for establishing linguistic conventions in populations of autonomous agents in a fully decentralised manner. As agents take part in local communicative interactions, they gradually establish a common conceptual system and vocabulary that enables them to communicate about arbitrary entities in their continuous environment. Apart from introducing the methodology, we also present six experiments that showcase the robustness of the methodology against sensor defects, its ability to handle noisy observations and uncalibrated sensors, and its suitability for continual learning.

KEYWORDS

language emergence; multi-agent systems; autonomous agents; emergent communication; self-organisation; language evolution

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1 INTRODUCTION

The field of emergent communication investigates how populations of artificial agents can collaboratively solve tasks by developing communication protocols that evolve through processes of interaction and adaptation. In recent years, the multi-agent reinforcement learning (MARL) framework has been adopted to tackle this challenge [3–6, 10–12, 14–17, 19, 22, 24, 33, 37]. While impressive results have been achieved within the MARL framework, the experimental setups in these studies often deviate significantly from how languages emerge and evolve in humans [34]. For example, some experiments involve only two agents [4, 12, 22], restrict agents to either speaking or listening [6, 7, 15, 19], or learning is not decentralised [11, 14]. In contrast, our objective is to facilitate language emergence through self-organisation, drawing inspiration from the language game experimental paradigm [27] and prior research on the emergence of perceptually grounded vocabularies [1, 2, 18, 20, 21, 23, 25–32, 34–36, 38, 39].

This paper introduces a methodology to establish, in a fully decentralised manner, a linguistic convention within a population of autonomous agents that enables the agents to refer to arbitrary entities in their environment. As they take part in local communicative interactions, agents gradually build up a linguistic inventory consisting of word forms associated with conceptual representations. Our contribution surpasses previous efforts in the language game paradigm as the methodology achieves three properties at once: decentralised, communication-based concept learning (i) in continuous feature spaces (as opposed to the discrete setting in [38]), (ii) in multi-agent emergent settings (as opposed to the tutor-learner setting in [21]), and (iii) with direct applicability to any dataset characterising entities in terms of continuously-valued features. An extended version of this paper is available at https://arxiv.org/abs/2401.08461.

2 METHODOLOGY

Autonomous agents are endowed with sensors to perceive their environment. However, due to variations in hardware, noisy observations, uncalibrated sensors, and potential sensor defects, a misalignment can emerge in the information perceived by individual agents. To address this mismatch, agents create abstractions in the form of concepts. Rather than directly transmitting sensor values, agents learn to communicate by associating words with internal learned conceptual representations. These representations, unique to each agent, serve as a bridge between the raw sensor data and an emergent linguistic convention [21]. Agents start out with an empty linguistic inventory, i.e. there are no predefined

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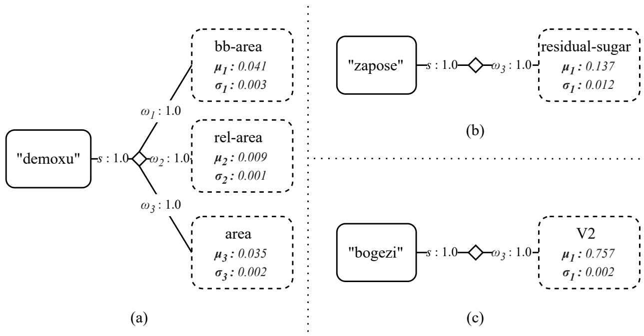

Figure 1: Examples of emerged concepts for the CLEVR (a), WINE (b) and CREDIT (c) datasets.

concepts or words. As they take part in pairwise, local communicative interactions, agents gradually build up this personal linguistic inventory.

In our methodology, the conceptual representation consists of a set of weighted Gaussian distributions, inspired by [21]. The agent's sensors perceive each entity within the environment, producing a set of values. These values are encapsulated by individual Gaussian distributions, each representing the sampled values from a specific sensory channel. The weight associated with each distribution signifies the importance of each sensor to the conceptual representation.

The agents employ a discrimination-based strategy, which focuses on constructing conceptual representations that enable effective differentiation of objects based on their distinct attributes. In each interaction, two randomly selected agents from the population assume the roles of speaker and hearer. The goal of the speaker is to draw the attention of the hearer to a specific object. To achieve this, the strategy involves creating representations that combine attributes that facilitate the discrimination between objects. Critically, the representation is bidirectional as it can be used to both produce and understand utterances in communication. After each interaction, the speaker provides feedback to the hearer by revealing the intended topic. Depending on the outcome of the game, the agents independently update their knowledge by adjusting their conceptual representations. As agents engage in iterative interactions, they progressively refine their representations and communicate more effectively. Over time, this dynamic process gives rise to the emergence of linguistic conventions within the population. Our methodology introduces novel invention, adoption, conceptualisation and alignment mechanisms for constructing such representations in a fully decentralised manner.

3 EXPERIMENTAL VALIDATION

We experimentally validate the effectiveness, flexibility, and robustness of our methodology using three large tabular datasets. These datasets cover three different types of domains. The CLEVR dataset consists of 85k visual scenes of geometric objects [13], the WINE dataset consists of physicochemical analyses of Portuguese wines [8], and finally the CREDIT dataset consists of approximately 250k principal component analyses of credit card transactions [9]. Each row of a dataset represents an entity in the agents' environment.

We conduct six different experiments. The first baseline experiment demonstrates the methodology's effectiveness on the three datasets. After 1 million interactions, the population can successfully communicate ±99.6% of the time on all three datasets. The second experiment tackles compositional generalisability by applying our methodology to a modified version of CLEVR (CoGenT) [13], showcasing the emergent concepts' adaptability to previously unseen attribute combinations. The third experiment extends the evaluation to heteromorphic populations, revealing that even when agents possess varying sensor combinations, a high degree of communicative success is still achievable. The fourth experiment tests the methodology's resilience against sensor defects, demonstrating its robustness in the face of sudden malfunctions and highlighting the lasting benefits of an established linguistic convention. The fifth experiment explores the methodology's robustness against differences in agents' perception. Lastly, the sixth experiment focuses on continual learning, confirming the methodology's adequacy and resistance to catastrophic forgetting.

Figure 1 depicts three concepts that emerged in the first baseline experiment. We only visualise feature channels with positive weights. Through a qualitative analysis, the emerged concept "demoxu" (see Fig. 1a) is found to be primarily used by agents to refer to small objects in the CLEVR environment. Likewise, "zapose" (see Fig. 1b) is used by agents to refer to "medium-sweet" wines in the WINE environment. Finally, "bogezi" (see Fig. 1c) emerged to refer to a particular kind of credit card transaction. While this concept remains transparent, it is not interpretable by humans due to its grounding in principal component analyses. This example demonstrates the usefulness of a self-organising system with emergent conventions. In such a system, agents are not limited to existing words but are able to create and adapt a convention that is tailored to their sensory endowment and their communicative needs.

4 CONCLUSION

In this paper, a novel methodology is presented for the emergence of communicatively effective, robust, and adaptive linguistic conventions among autonomous agents. The methodology facilitates the decentralised emergence of linguistic conventions through local, task-oriented interactions between pairs of agents, resulting in symbolic labels associated with concept representations grounded in a multi-dimensional, continuous feature space. These associations are individually constructed by agents, yet compatible on a communicative level. The methodology is validated through experiments across three diverse datasets, showcasing its effectiveness in various domains. We introduce a model for the emergence and evolution of linguistic conventions in populations of autonomous agents which is applicable to any dataset that characterises entities using continuously-valued features.

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