1S-03

# Dynamic Vocabulary Size Scheme in Emergent Communication Systems

コミュニケーション発生システムにおける拡張可能な語彙モデル

Trisitichoke Tasavat　　鶴岡 慶雅

The University of Tokyo

**Introduction**

The research area of *Emergent Communication* (EC) has gained attention from many researchers in recent years. Emergent Communication is a research area that focuses on grounding communication protocols among agents in a multi-agent setting. In other words, it encourages agents to develop their own language from scratch. It achieves this goal by training agents to communicate to solve a cooperation task.

An example of such a communication task is a *Referential Game*, shown in Figure 1. There are two agent roles in this task: *a speaker* and *a listener*. The listener observes multiple object images. All objects are different in their shapes and colors. Among all images, only one is a target image, while the other images are distractors. Without information about which image is the target image, the listener's role is to choose the target image. On the other hand, the speaker agent observes only the target image and must convey the information about the target image via a message, through a communication channel. Both agents only receive rewards if the listener can correctly choose the target image. Therefore, they must settle on particular communication protocols if they want to perform better than random guessing. Concretely, the speaker's message must convey properties of the target image (e.g., "blue sphere," "red cylinder," etc.). Fortunately, by adopting a learning algorithm, such as reinforcement learning, we can train agents to solve this referential game. The emerged communication protocols are the target of interest in EC research.

This paper focuses on a particular aspect of EC research, vocabulary size, the number of available symbols that agents can use to compose a message (not to confuse with the *length* of the message). As far as the authors know, it is typically treated as a hyperparameter that needed to be manually tuned. This paper proposes Dynamic Vocabulary Size scheme, which allows agents to expand the vocabulary size autonomously. It also shows that by adopting DVS, agents reach stable communication protocols faster, and the emerging communication protocols are more *compositional* than their counterparts.

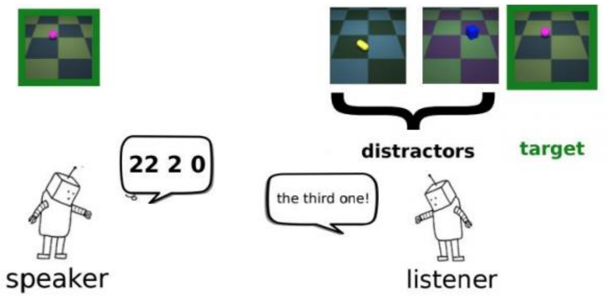


Figure 1: An example of a Referential Game. Retrieved from [1]

**Proposed method**

Dynamic Vocabulary Size scheme is built upon two foundations:

1) It represents vocabularies as a graph structure, where each symbol in the vocabulary is a node in the graph. It generates a message from this graph with a *Gated Graph Sequence Neural Network* [2]. Graph structure allows a new symbol to be appended with ease, compared to the common architectures like a recurrent neural network where the output size is fixed. A graph structure could also help induce a weak structural bias to overall vocabularies, as the edges among nodes are also trainable. The structural bias should lead to communication protocols with a higher degree of compositionality.

2) It adopts Zipfian distribution as a trigger criterion for appending a new symbol to the vocabularies. Concretely, it assumes that the rank-frequency distribution of symbols that appeared in the speaker's messages follows a particular Zipfian distribution. During training, if a vocabulary size is too small, each symbol's appearance frequency would be relatively close to each other as the speaker needs to utilize all the symbols as much as possible. This results in a very flat rank-frequency distribution. Therefore, when a symbols' rank-frequency distribution starts to differ (becomes flatter) than a predefined distribution, agents automatically add a new symbol to the vocabulary (in other words, adding a new node to the vocabulary graph).

## Experiment

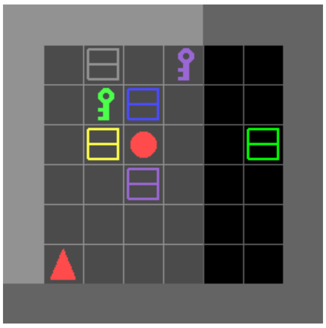

Figure 2: BabyAI, a task used in the experiment [3]

The experiment in this paper also follows the Referential Game template explained earlier. As shown in Figure 2, the listener (triangle at the lower-left corner) is placed in a mini-grid environment, adapted from BabyAI [3]. There are multiple objects aside from the listener, each of which differs by shape and color. The task's objective is that the listener moves to a specified object (e.g., a red ball) as fast as possible. Indeed, the listener has no information on which object is the target and obtains the information by interpreting the speaker's message. The speaker lies outside the environment. It observes the mini-grid observation at the potential final state as an instruction. For instance, if the objective of an episode is that the listener moves to the red ball, the speaker observes the state where a listener has already moved to the red ball, but types of distractors and object placements are entirely different. This is to prevent the speaker from cheating by conveying only the grid location where the listener has to move to.

With this experiment setting, we compare the proposed method with the baseline on two aspects:

1) *Sample efficiency*: similar to a typical RL task, it evaluates how fast agents learn the task. In EC, it also means how fast the agents reach the stable communication protocols.

2) *Compositionality*: since the target objective is by nature compositional (shape + color), the speaker message could also possibly be compositional (i.e., the message could be divided into sub-meanings). For the quantitative measure of compositionality, we adopt *Tree Reconstruction Error* [4] (the lower, the better).

For the baseline, we adopt Gated Recurrent Unit as a message generator module of the speaker model. Thus the vocabulary size of the baseline is fixed.

## Results

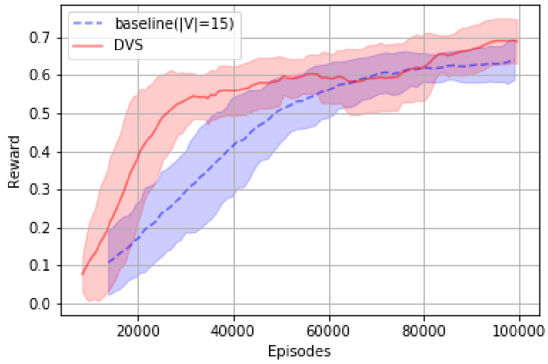


Figure 3: Reward plots of the speaker with DVS and baseline

Table 1: Tree Reconstruction Error

| | DVS | Baseline | Random |
|---|---|---|---|
| TRE | **1.69** | 2.28 | 5.10 |

Figure 3 shows training rewards for the speaker with DVS implemented and the baseline speaker (vocabulary size = 15). The speaker with DVS reaches stable communication protocols faster, and at the same time, the vocabulary size in the first 30,000 episodes rises from 5 to 13 and stays still afterward. As for the compositionality, TRE measure is shown in Table 1. It shows that the speaker with DVS also results in communication protocols with a higher degree of compositionality than the baseline.

## Conclusion

This paper proposes a Dynamic Vocabulary Size (DVS) scheme for Emergent Communication systems in which agents autonomously expand their usable vocabularies when they learn to communicate with each other using a sequence of discrete symbols. With a DVS, agents reach a stable communication protocol faster, and the emerged communication protocol is more compositional than those of the fix-sized vocabulary scheme counterparts.

## References

[1] Lazaridou, Angeliki, et al. "Emergence of linguistic communication from referential games with symbolic and pixel input." arXiv:1804.03984 (2018).
[2] Li, Yujia, et al. "Gated graph sequence neural networks." arXiv:1511.05493 (2015).
[3] Chevalier-Boisvert, Maxime, et al. "BabyAI: First steps towards grounded language learning with a human in the loop." arXiv:1810.08272 (2018).
[4] Andreas, Jacob. "Measuring compositionality in representation learning." arXiv:1902.07181 (2019).