

# GENERATION OF STRUCTURED SPATIAL PATTERNS THROUGH ADVERSARIAL IMITATION LEARNING

Hiroyuki Iizuka<sup>\*1,2</sup>, Wataru Noguchi<sup>1</sup>, Taiki Sasaki<sup>3</sup> and Masahito Yamamoto<sup>1,2</sup>

<sup>\*</sup>Corresponding Author: iizuka@ist.hokudai.ac.jp

<sup>1</sup>Faculty of Information Science and Technology, Hokkaido University, Sapporo, Japan

<sup>2</sup>Center for Human Nature, Artificial Intelligence, and Neuroscience,  
Hokkaido University, Sapporo, Japan

<sup>3</sup>Graduate School of Information Science and Technology,  
Hokkaido University, Sapporo Japan

This study shows that systematic structures that appear in language and birdsong can be generated by adversarial imitation learning, in which one wants to imitate the opponent's patterns without the opponent imitating their patterns. In prior adversarial imitation studies, the generated patterns became chaotic but not structured. Therefore, we extended a previous model using the concept of generative adversarial networks (GANs) for deep learning. The agents were modeled using generator and discriminator networks. Our results show that mutual adversarial imitation learning can lead to higher fractal dimensions of the generated patterns and cause the structurization of patterns.

## 1. Introduction

Aside from being a complex time-series pattern, a language also features a systematic structure or grammar (Chomsky, 1965). Such a structure can be observed in the time-series of the bird songs (Honda & Okanoya, 1999), the close calls of banded mongoose (Jansen et al., 2012) and the humpback whale songs (Cholewiak et al., 2013) as well as in the behavior patterns of macaque monkeys (Hihara et al., 2003) and degus (Tokimoto & Okanoya, 2004) and even in spatial patterns (Kondo & Miura, 2010).

To determine how systematic structures emerged, Kirby et al. conducted experiments from a linguistic perspective (Kirby et al., 2008, Cornish et al., 2013, Winters et al., 2015). These experiments showed that linguistic structures emerge in the trade-off between learnability and expressivity through cultural transmission, in which symbols are remembered and then transmitted to others

repeatedly (remembering here is equivalent to what we call imitation). However, these experiments required the assignment of distinct random sequences for each expression at the initial stage in order to produce structured sequences. If the initial sequences are equivalent among all expressions, the sequence is simply transmitted without any structuring, and the system has no expressivity. This means that other principles are needed to explain how the complexity required to produce structural patterns emerges.

Accordingly, we hypothesize that patterns generated by organisms become complex and structured through adversarial situations, in which one wants to imitate or understand an opponent's signal patterns without the opponent imitating or understanding their own signal patterns. For example, the ability to imitate the profitable behavioral patterns of others leads to one's own benefits. In contrast, this may remove these benefits from those who are being imitated. In other words, the strategy of imitating others while avoiding being imitated by others may be evolutionarily dominant. Furthermore, individuals may want only those in their in-group to understand profitable signals, which requires secrecy. We believe that the complexity generated by interspecific adversarial communication is adopted for intraspecific cooperative communication, which in turn leads structured communication to evolve.

Based on this concept, we propose a simulation model that complexifies time-series patterns through adversarial imitation learning. Although the original model only produced chaotic behavior in time-series (Yamazaki et al., 2020), we extended it by introducing the recognition of patterns by individuals, thus showing that recognition leads to simplification and pattern structuring, rather than mere complexity.

## **2. Simulation model**

In the field of machine learning, generative adversarial networks (GANs) can imitate real data (e.g., images) to generate realistic artificial data (Goodfellow et al., 2014). GANs produce high-quality imitation data using a generator and a discriminator that features adversarial learning. We used GANs to model a situation in which two individuals, Agents 1 and 2, are engaged in adversarial imitation learning. Unlike the study upon which our work is founded, we introduced the recognition of a discriminator to evaluate the imitation's success (Suzuki & Kaneko, 1994, Yamazaki et al., 2020).

An overview of the proposed model is presented in Fig. 1. Each individual consists of a generator (G1/G2) and a discriminator (D1/D2). The discriminator determines whether a pattern (G1(Z) or G2(Z)) is produced by its own generator

or the opponent's generator. The generator learns to generate a pattern such that its own discriminator can easily recognize the pattern as being generated by itself. This learning process works toward simplifying the pattern to facilitate recognition. Furthermore, the generator learns to trick the opponent discriminator by recognizing patterns produced by the opponent generator. Consequently, the discriminator and generator learn to avoid being tricked by the opponent's generator, thus increasing pattern complexity. This learning process occurs under mutual conditions.

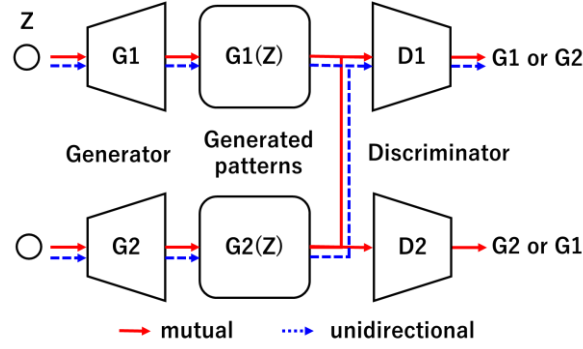


Figure 1. Overview of our model. G1/G2 and D1/D2 represent the generators and discriminators for Agent 1/2, respectively. Red and blue arrows indicate mutual and unidirectional adversarial imitation learning, respectively. The generators and discriminators are realized by deep neural networks with convolutions and de-convolutions. The generators receive random values as seeds to generate patterns, as in the original GAN. G1/2(Z) are the patterns created by Generators G1/2.

Both the generator and the discriminator are implemented with feed-forward neural networks, with initial parameters given randomly. Those parameters are trained by gradient descent. The loss function of Agent 1 can be expressed using hinge loss as follows:

$$L_{D1} = -E_{x \sim G1(z)}[\min(0, -1 + D1(x))] - E_{x \sim G2(z)}[\min(0, -1 - D1(x))], \quad (1)$$

$$L_{G1} = -E_{z \sim N}[\min(0, -1 + D1(G1(z)))] - E_{z \sim N}[\min(0, -1 + D2(G1(z)))], \quad (2)$$

The loss function of Agent 2 is identical apart from exchanging D1/D2 and G1/G2. When this function is minimized, the discriminator learns to output positive and negative values for the patterns created by its own generator and opponent generator, respectively, and the generator is trained such that both

discriminators output positive values. The batch size was set to 32, and one epoch represents a single parameter update by the losses computed using the 32 patterns produced by each generator.

To show that mutual adversarial imitation learning produces structural patterns, we compared its results to the unidirectional condition, where only one individual performs adversarial imitation learning. That model is denoted by blue arrows in Fig. 1. Under unidirectional adversarial imitation learning, there is no D2 discriminator, and the term D2 in Eq. (2) for  $L_{G1}$  and  $L_{G2}$  is omitted from the loss function.

### 3. Results

In our simulations, the model was trained for up to 5,000 epochs under both conditions. Figs. 2 and 3 show the patterns produced by each generator with eight different  $z$  values under the unidirectional and mutual conditions, respectively. Because all the network parameters were initialized with random values, the generated patterns became equally cluttered at the beginning for both conditions.

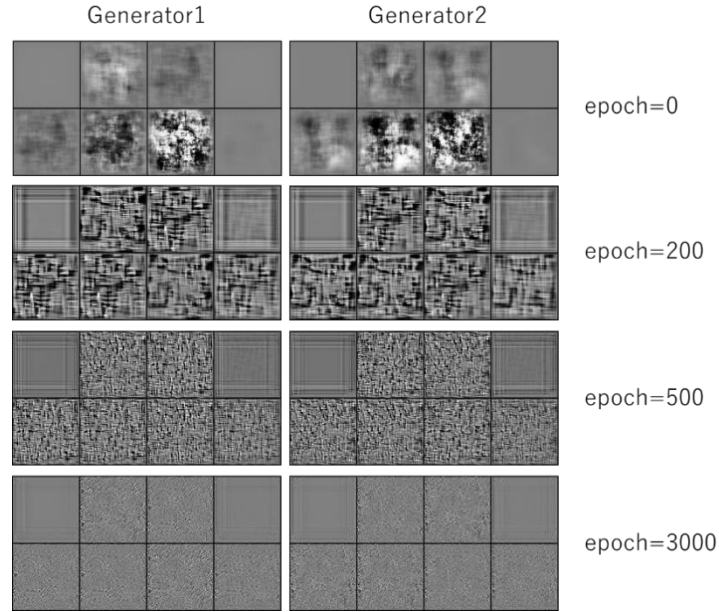


Figure 2. Examples of spatial patterns generated by G1 and G2 under unidirectional adversarial imitation learning. Each block has 8 patterns generated from 8 different  $z$  values.

However, as the learning process progressed, the generated patterns became increasingly locally detailed and cluttered in unidirectional adversarial imitation learning. Under mutual adversarial imitation learning, however, these patterns appear to have formed a sort of global pattern.

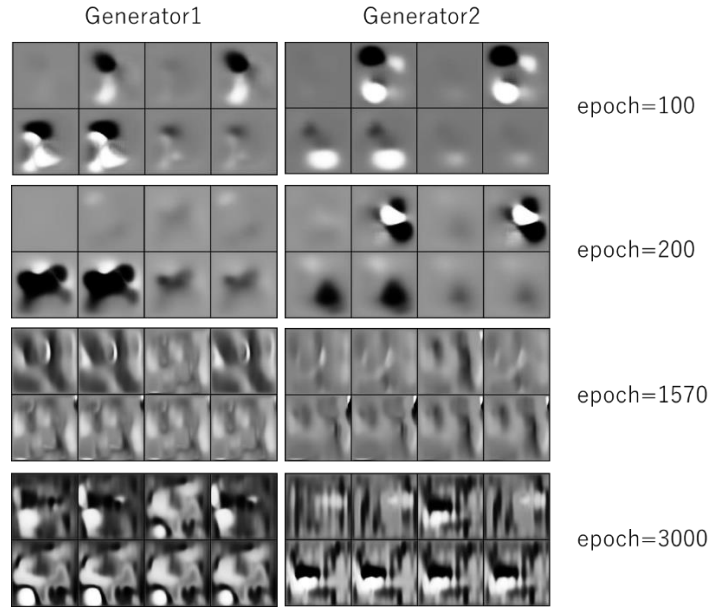


Figure 3. Examples of spatial patterns generated by G1 and G2 under mutual adversarial imitation learning.

To demonstrate the structuring progress under mutual adversarial imitation learning, we calculated the fractal dimensions of the generated patterns using the box-counting method with the patterns' binary representations and the grayscale median. We also calculated the entropy of the grayscale images to measure complexity. Figure 4 shows the fractal dimensions and entropies for mutual and unidirectional adversarial imitation learning. Here, entropy decreased in the early stages of learning but remained high thereafter. The fractal dimension also did not increase, instead converging to a low value. As can be seen in Fig. 2, as the learning progresses, the pattern becomes more cluttered, but lacks an underlying structure.

Under mutual adversarial imitation learning, however, the entropy and fractal dimension exhibited oscillation. The entropy decreased, and the pattern

became less cluttered, but the fractal dimension temporarily increased. Fig. 3 shows that the pattern was not merely cluttered but developed a structure. In the current simulation, this structure was not maintained, and the fractal dimension remained high. Nevertheless, the fractal dimension increased again, and structuring occasionally occurred. These results were confirmed through multiple simulations. Thus, our results show that mutual learning promotes the structuring of generated patterns.

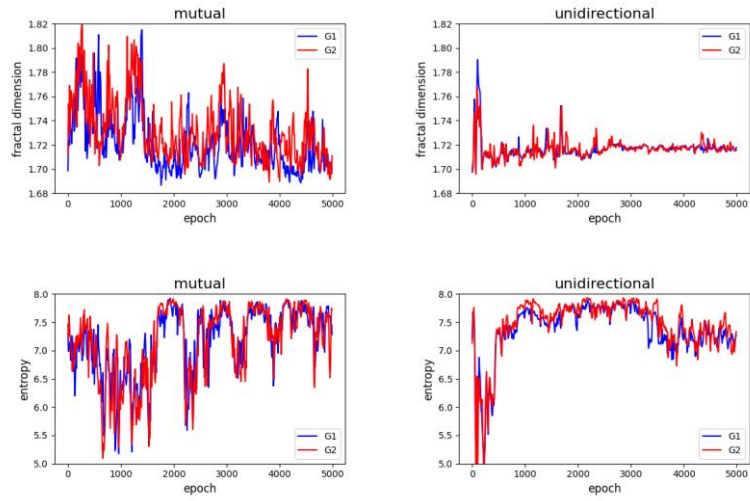


Figure 4. Changes in fractal dimensions and entropy of spatial patterns generated by G1 and G2. The left and right columns indicate learning results under the mutual and unidirectional conditions, respectively.

#### 4. Discussion

In the case of unidirectional adversarial imitation learning, the discriminator/generator pair of Agent 1 should learn to escape from patterns created by the opponent generator. It is sufficient to gradually make the patterns chaotic to prevent the opponent from successfully imitating them. Once complexity arises, structuring can occur as a result of simplifying pressures, so that the patterns can be easily recognized by one's own discriminator. This corresponds to Kirby's group experiment of structuring sequences to be easily remembered in the process of cultural transmission through the learning force. In our previous model, the generated patterns became chaotic; however, simplification did not occur, and no structured patterns were found (Yamazaki et al., 2020). In the present model, the introduction of a discriminator makes it

necessary to form patterns that are easy for the discriminator to recognize, which leads to pattern structuring. Because it is not sufficient for the generator to simply keep avoiding the opponent generator in mutual adversarial imitation learning, a stronger adversarial learning pressure was applied to the generators, resulting in structured patterns.

Our simulation results generated a high fractal dimension, indicating that the generated patterns had a recursive structure, similar to that of language. We believe that not only cooperative communication, but also adversarial communication was necessary to create such structures, which may have been incorporated into language.

### Acknowledgements

This work was supported by JSPS KAKENHI (grant number JP20H04989).

### References

- Beckner, C., Pierrehumbert, J. B., & Hay, J. (2017). The emergence of linguistic structure in an online iterated learning task. *Journal of Language Evolution*, 2(2), 160–176.
- Cholewiak, D. M., Sousa-Lima, R. S., & Cerchio, S. (2013). Humpback whale song hierarchical structure: Historical context and discussion of current classification issues. *Marine Mammal Science*, 29(3), E312-E332.
- Chomsky N. (1965) Aspects of Theory of Syntax. Cambridge (MA): The MIT Press
- Cornish, H., Smith, K., & Kirby, S. (2013). Systems from sequences: An iterated learning account of the emergence of systematic structure in a non-linguistic task. *Proceedings of the Annual Meeting of the Cognitive Science Society*, 35(35).
- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. *Advances in Neural Information Processing Systems*, 27.
- Hihara, S., Obayashi, S., Tanaka, M. and Iriki, A. (2003). Rapid learning of sequential tool use by macaque monkeys, *Physiology and Behavior*, 78, 427-434.
- Honda, E., & Okanoya, K. (1999). Acoustical and syntactical comparisons between songs of the white-backed munia (*Lonchura striata*) and its domesticated strain, the Bengalese finch (*Lonchura striata* var. domestica). *Zoological Science*, 16(2), 319–326.
- Jansen, D. A., Cant, M. A., & Manser, M. B. (2012). Segmental concatenation of individual signatures and context cues in banded mongoose (*Mungos mungo*) close calls. *BMC biology*, 10(1), 1-11.

- Kirby, S., Cornish, H., & Smith, K. (2008). Cumulative cultural evolution in the laboratory: An experimental approach to the origins of structure in human language. *Proceedings of the National Academy of Sciences*, 105(31), 10681–10686.
- Kondo, S., & Miura, T. (2010). Reaction-diffusion model as a framework for understanding biological pattern formation. *Science*, 329(5999), 1616-1620.
- Suzuki, J. and Kaneko, K. (1994). Imitation games. *Physica D: Nonlinear Phenomena*, 75(1–3):328–342.
- Tokimoto, N., & Okanoya, K. (2004). Spontaneous construction of “Chinese boxes” by Degus (*Octodon degu*): A rudiment of recursive intelligence? *Japanese Psychological Research*, 46(3), 255-261.
- Winters J., Kirby S., Smith K. (2015). Languages adapt to their contextual niche, *Language and Cognition*, 7(03): 415–49.
- Yamazaki, S., Iizuka, H., & Yamamoto, M. (2020). Complexity of bird song caused by adversarial imitation learning. *Artificial Life and Robotics*, 25(1), 124–132.