Life as an emergent phenomenon: studies from a large-scale boid simulation and web data

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A large group with a special structure can become the mother of emergence. We discuss this hypothesis in relation to large-scale boid simulations and web data. In the boid swarm simulations, the nucleation, organization and collapse dynamics were found to be more diverse in larger flocks than in smaller flocks. In the second analysis, large web data, consisting of shared photos with descriptive tags, tended to group together users with similar tendencies, allowing the network to develop a core–periphery structure. We show that the generation rate of novel tags and their usage frequencies are high in the higher-order cliques. In this case, novelty is not considered to arise randomly; rather, it is generated as a result of a large and structured network. We contextualize these results in terms of adjacent possible theory and as a new way to understand collective intelligence. We argue that excessive information and material flow can become a source of innovation.

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1. Introduction

This paper discusses life as an emergent phenomenon. To this end, an emergent phenomenon is defined as
the macroscopic layers of patterns and structures that appear as a result of cooperative phenomena between autonomously behaving elements. A group of elements creates a self-organizing structure, which governs the individual micro rules and creates a new macro structure. Therefore, consecutive micro–macro recurrent self-organization is defined as an emergent phenomenon.

For example, David Christian states that emergence is the deepest and most beautiful concept in science [1]. Steven Johnson interprets emergence more widely, extending it to a phenomenon occurring in a human community [2]. Stuart Kauffman advocates for the idea of the adjacent possible [3,4] to advance the understanding of emergent phenomena, and he references it as a source of biological evolution. Specifically, in that interview, he claims that a biosphere can be viewed as a secular or long-term trend and it can maximize the rate of exploration of the adjacent possible of an existing organization.

In this paper, we discuss the concept of emergent phenomena based on the results of a concrete simulation and analysis of large web service data, by referring to their relation to adjacent possible theory.

Self-organization is similar to but different from emergence. The self-organization of structures and patterns has been well studied in various fields of physics and chemistry. For instance, examples of well-known cooperative phenomena include the transition phenomenon of a laminar flow pattern to a turbulent flow, as indicated by a fluid mechanical system, and various types of phase transition phenomena exhibited by a magnetic spin system. In some magnetic materials, it is known that hierarchical ordered magnetic spin structures appear to be random in a spatial direction, while the temporal correlation is sustained and organized (called spin glass).

Examples of these types of self-organization phenomena are common in the natural world. These shape and pattern formations are considered to be typical examples in life and non-life systems, although we still cannot spontaneously generate life from non-living matter. Therefore, this raises the question of whether we can capture life phenomena as examples of self-organization, or whether we need to create a new theory to understand those phenomena.

An emergent phenomenon is an extension of this self-organization phenomenon. However, there are some differences between them. Self-organization is the one-way formation of macroscopic order from micro dynamics, whereas emergent phenomenon is the circulation of recurrent information from macro to micro, and vice versa. For example, society changes by developing new technologies, and research needs change as society changes, which creates new devices. Consequently, society changes again. Examples of this process in relation to emergent phenomena include the computer, the Internet, the iPhone and so on. The self-organization phenomenon refers to ubiquitous phenomena exhibited by open, non-equilibrium, nonlinear systems, whereas emergent phenomenon sequentially repeats self-organization, which accompanies the updating of the micro rules that underlie self-organization.

However, the emergence-creating mechanism has not yet been identified. The more we explore the condition of emergence, the more we see that true emergence can only be found in evolutionary life phenomena. Evolutionary phenomena, or their products, indicate emergent phenomena. In the case of an evolutionary phenomenon, a certain pattern is born; then, a new pattern evolves based on that pattern, which will recur many times. What condition should be imposed on each element in order to facilitate the successive evolution of the pattern-generating patterns? Does this correspond to what adjacent possible theory demands, as Stuart Kauffman, Steven Johnson and others claim? In order to explain emergent phenomena, this paper will discuss two examples: the evolution of a large simulated swarm and the evolution of a web service. Both are examples of collective phenomena produced by large agent groups; the first example is a computer simulation of the order of 1 million, while the latter is an analysis of a large amount of web service data generated over the last 3 years.

2. The complexity of a large swarm

In this section, we demonstrate a simple computational model of the flocking behaviour of agents (boids) [5]. As the size of the flock increases, it shows a different complexity; large, self-organized
Flocks are intrinsically unstable, and they will spontaneously collapse and reorganize, repeatedly. The sizes, forms and dynamics differ from one flock to another. When we increase the number of agents, new flocks emerge. Assuming that many agents live in a large space, different flock forms will spontaneously organize in different spatial locations. Later, we will discuss why the interaction of different flocks and their dynamics is a cornerstone of emergent phenomena.

To simulate flocking behaviour, we used a simple model, called a boid model, proposed by Craig Reynolds in 1987 [6]. In this model, each individual is an oriented boid navigating in three-dimensional space according to the following three rules: (i) they attract each other, (ii) they separate from each other, and (iii) each orientation is aligned (i.e. the direction of the velocity vector).

Each of these three rules has a total of nine parameters that determine the relative attraction/repulsion strength of the force and the area to which the force will be determined; when this is changed, various swarming patterns appear. There are various ways to implement these three rules, and we assume that the emerging pattern will not be changed significantly by its implementation method.

In the original model simplification performed by Vicsek [7], the first and second rules mentioned above are eliminated; the third rule is kept, and, instead, noise is added to the agent motion equation. Still, it is possible to grasp the aspect of making a flock, and, based on that, Toner et al. [8] succeeded in handling analytical fluid dynamics by taking an infinite limit; thus, they described swarming behaviour as the average particle density and velocity. They discovered the emergence of the swarming and non-swarming phases. Various studies [9–12] have been conducted since Vicsek’s and Toner’s successful re-formalization of Craig’s model.

Here, we propose the ordinary differential equation of motion (2.1), which holds three rules based on Reynolds’ original boid model, but on a large scale:

\[
\Delta v_i = W_{\text{att}} \cdot \left( x_i - \frac{\sum_{j \in S_{\text{att}}} x_j}{n_{\text{att}}} \right) + W_{\text{rep}} \cdot \left( \sum_{j \in S_{\text{rep}}} \frac{(x_i - x_j)}{|x_i - x_j|} \right) + W_{\text{ali}} \cdot \left( v_i - \frac{\sum_{j \in S_{\text{ali}}} v_j}{n_{\text{ali}}} \right). \tag{2.1}
\]

The position of each boid \(x_i\) is updated based on the computed velocity, \(v_i\), iteratively. The attraction, repulsion and alignment terms are represented by the first, second and third terms, respectively. Each rule has an interaction range around each agent, as denoted by \(S_{\text{att}}\), \(S_{\text{rep}}\) and \(S_{\text{ali}}\), respectively. In the equation, we also introduce the amplitudes of those interactions as \(W_{\text{att}}\), \(W_{\text{rep}}\) and \(W_{\text{ali}}\), respectively. The interaction ranges, with a three-dimensional circular sector of their angles towards the front, are denoted as \(\pi/2\), \(\pi/2\) and \(\pi/3\), respectively. In order to avoid any excess increase or decrease in speed, we bound the amplitude of speed between \(V_{\text{min}}\) and \(V_{\text{max}}\).

Furthermore, while limiting the total number of boids to a finite size, we calculated the behaviour when the size increased up to 1 million orders. By doing this, we studied the swarming (flocking) dynamics as an emergent phenomenon, and we discuss its complexity below. As the total number of boids increases from 2048 to 524288, while maintaining a constant density, the flock’s appearance changes (figure 1). In order to compute large swarming behaviour, we parallelized the computational steps using the general-purpose computing on graphics processing units (GPGPU) method [13]. Because our boid model has a finite interaction range, the computation cost was reduced significantly. A boundary condition uses a three-dimensional periodic boundary. Swarming dynamic destabilization begins when the size is above 10000. A flock of round chunks and a narrow swell, like a snake, appear in the larger flock swarms. The flocks are widely distributed in space when enough agents exist and interact with each other.

The following subsections address how we can identify each flock and then how we can analyse each flock’s fluctuations, as well as how complexity evolves by increasing the total number of agents.
Figure 1. Snapshots of swarming behaviour. The total number of boids in each panel is (a) 2048, (b) 16384, (c) 131072 and (d) 524288, respectively. Some flocks are composed of a very large number of boids with narrow filament patterns. The following parameters were used in the simulation: $S_{\text{att}} = 0.05$, $S_{\text{rep}} = 0.01$ and $S_{\text{ali}} = 0.05$, and $W_{\text{att}} = 0.002$, $W_{\text{rep}} = 0.008$ and $W_{\text{ali}} = 0.06$, measured in a dimensionless unit. The interaction ranges, with a three-dimensional circular sector of their angles towards the front, are $\pi/2$, $\pi/2$ and $\pi/3$, respectively. The initial velocity of each boid is set at random, and the density of the total number of boids is kept constant at 16384 (number per cubic unit). The minimum and the maximum speed are set at 0.001 and 0.005 (unit per step), respectively. (Online version in colour.)

(a) The difficulty in identifying different flocks

It is important to note that it is difficult to identify different flocks. If only a single stable flock exists, it is easy to identify it. However, in the case discussed in this paper, a spatio-temporal flock pattern oscillating between genesis and extinction was observed. We identified the boundary of each flock algorithmically (figure 2). This was done using the density-based spatial clustering of applications with noise (DBSCAN) algorithm [14]. This algorithm requires that all individual boids belonging to the same flock have at least one other boid in the neighbourhood, which is intuitive to our definition of a flock.

As a result of this identification method, we noticed that the same boids do not maintain the same flocking unit constantly. Alternatively, we found a sort of ‘individual metabolism’, whereby a certain percentage of boids are constantly leaving the flock as new ones join. In very large flocks, on average, 20% of all boids are swapped per 100 time steps. By contrast, the fluctuation
in the flock size is only around 2%. This is not the case for smaller flocks. However, it should be noted that this tendency is observed only in the parameter area allowing for the coexistence of small and large flocks. Therefore, we hypothesize that flocking behaviour principally preserves intrinsic instability. If a flock can preserve instability, it becomes sensitive to noise, and a minute perturbation will be amplified to the flock scale. For example, flocks can take collective action when being attacked by predators. This picture seems to be universal regardless of real or virtual differences in the types of swarms. In the end, we tend to think that a flock is self-organized by individual boids, but the flocking behaviour actually comes first, and it is divided into each boid’s individual behaviour. Actually, as seen in figure 1, flocks, such as filaments, lead to individuals having the same direction of velocity, while large flocks lead to individuals walking randomly. Owing to the micro-individual boid and the entire macro-flock feedback effects, we concluded that individual flocking is a good example of emergent dynamics.

(b) Fluctuation differences based on flock size

When considering flock information transmission, if we take the analogy of sound speed in fluid mechanics, density and speed fluctuations are the information carrier candidates in linear approximation. We calculated the covariance between two boids in order to measure each swarm size’s ease of response to the external field. As shown in figure 3, we computed the flock’s susceptibility (i.e. velocity and density fluctuation) using the following equations (2.2) and (2.3) [15]. The sum is taken for every pair \((i, j)\) within the correlated range \(r_C\) (judged from the range where the maximum value becomes halved). The velocity fluctuation \(X_v\) is computed by

\[
X_v = \sum_{i \neq j; r(|i-j|) \leq r_C} N_p^{-1} \delta v_i \delta v_j \tag{2.2}
\]

and

\[
\delta v_i = v_i - \frac{\sum s v_s}{N}, \tag{2.3}
\]

where \(\delta v_i\) is a deviation of the \(i\)th boid from the averaged velocity.

Here \(N\) is the flock size and \(N_p\) is the number of pairs within the correlated range \(r_C\). The density fluctuation \(X_n\) is computed using two steps. First, by taking the small region (a cubic mesh of the size \((2/30)^3\)), we computed the number of total regions \((N_m)\) and the pair number of regions \((N_{mp})\) within the correlated region \(r_{dc}\) of each flock \(m\). We then computed the density.
fluctuation $\delta n_k$ for each region $k$. Finally, we compute the correlation between those fluctuations:

$$N_{mp} = \sum_{k \neq l; r(k,l) < r_{dc}} 1,$$

$$\delta n_k = n_k - \frac{\sum_j n_j}{N_m},$$

and

$$X_n = \sum_{k \neq l; r(k,l) \leq r_{dc}} N_{mp}^{-1} \delta n_k \delta n_l.$$

After computing the density fluctuation and velocity fluctuation correlation, it was found that the latter fluctuation (velocity fluctuation) was greater in the smaller flocks and the former fluctuation (density fluctuation) was greater in the larger flocks. This implies that swarm fluctuations can vary depending on the size of the flock. Those fluctuations reflect the different micro dynamics of the boids underlying the macro-flocking dynamics.

(c) **Will the complexity increase as the overall size increases?**

Using a compression algorithm known as bzip, we tried to compress the swarming behaviour snapshots into relatively short time scales [16]. As seen in figure 4, this is plotted against the entire boid size. As shown, the compressibility increases as the total number of boids increases. As one’s interpretation is to increase the size while keeping the density of the boids constant, increasing the size complicates the swarm pattern; thus, the flock behaviour does not have scalability. As a comparison, we also computed the same compression of random walkers, which is not proportional to the number of agents, but which is constant.

(d) **Why this phenomenon occurs**

Increasing the number of boids means increasing the degrees of freedom (DOF) for the entire system. Consequently, complex latent movements in the lower DOF will emerge in the higher DOF. As the number of boids increases, a large flock is formed, which in turn changes the behaviour of the boids that exist outside the flock, resulting in different movement overall. This complexity becomes invisible by taking the statistical mechanical or the thermodynamic limit. In the large boid model, we observed that various approximations are only meaningful when there are weak bonds among the homogeneous elements, but the most interesting phenomena come from the mid-size flocks (i.e. a very large, but not infinite, size) in the transient time scale. After a long period of time, a large flock will break up; thus, large flocks are in a long transient state. Owing to the periodic boundary condition, the boids will come back again to organize flocking
behaviour after approximately 50 000–100 000 time steps for 1000 000 boids. With different sets of parameters, flocking behaviours become very stable, but this occurs in small-sized flocks (size of 100 orders); no stable large flock will emerge. The thermodynamic limit is the nature of the system at infinite time and infinite system size. The flock dynamics discussed in this paper occur in the transition state, which cannot be discussed as a thermodynamic limit. When taking the hydrodynamic limit, we can describe flocks using the average speed and the density, but then we cannot simulate the dynamics in which linear flocks will pop out from a large flock and, eventually, destroy it. In any case, while the complexity of the flocking behaviour observed in this study is a consequence of the large flock structure, it will not entirely stabilize the individuals’ dynamics. In other words, instability at the individual level is preserved and can be amplified up to a macro scale. So statistical stability is not guaranteed.

Therefore, we can say that the complexity, and thus the related emergent phenomenon, is observed in a finite space and time scale. Even the parameter region where no complex swarm, ultimately, is retained, shows very interesting transient state behaviour. In the next section, we further expand this picture in a real-world open, large-sized web network.

3. Complexity in large web data

As opposed to computer simulations, real life provides sufficient complexity and large data flows to conduct an effective analysis. The data from a large web service is an example of a scenario with real-life complexity [17,18]. In this section, we discuss a large web service’s time evolution using the entire dataset from RoomClip, a social network service. The dataset was compiled from March 2012 to May 2015, after the service’s launch. We will also discuss the results of the analysis from the emergent phenomenon viewpoint.

RoomClip users post photos of a room together with a set of tags (e.g. living, entrance, bedroom). For each post, users can follow other users and attach ‘likes’ to the posts. Everyone can see the list of tags used in each photo and search the site according to the tags. Since the service’s launch, the number of users (410 000 users as of April 2015) and the number of photos (1 million as of April 2015) have increased, as shown in figures 5 and 6.

(a) Temporal development of the number of ‘likes’

The number of RoomClip users gradually increased, and the activity of all the service’s ‘likes’ demonstrates that the number of postings also increased [19,20] (figure 6). In particular, when we
look at the individual tags, the temporal dynamics show a discontinuous and rugged increase (not shown here).

Therefore, as we saw in the boid simulation, this activity is not caused by the group-size increment alone. However, because the total number of users exceeded a certain threshold, a sudden increase in the number of tags occurred within a specific point in time. The act of attaching ‘likes’ provides a feedback effect to other users observing it. Thus, it becomes easier for people to attach a ‘like’ as more ‘likes’ are attached. Such a positive feedback effect can be analysed using the Hawkes process [21], which adds a feedback effect to the Poisson process. This is akin to the preferential attachment observed in aggregation patterns. The rate of posting ‘likes’ by the user $k$ at time $t$, which is given by $\lambda^k(t)$, is given as follows:

$$
\lambda^k(t) = \lambda_0^k(t) + \sum_{k'} \int_{0}^{\infty} h^{k'}(t-\tau) \lambda^{k'}(t-\tau) \, d\tau,
$$

(3.1)

where the first term describes the default activity rate and the second term describes the inter-user network activity. Here, the function $h^{k'}(t-\tau)$ expresses the contribution from user $k$ to user $i$ with a time delay $\tau$. We used the simple form, $h(t) = \alpha \exp(-\beta t)$, as the function to fit the time series users’ ‘like’ events (users that posted more than 300 posts) by maximizing their likelihood function [22]. We found that the integrated response function occasionally displays sharp bursts,
Figure 7. Time evolution of the default activity rate (grey line, left axis) and the inter-user network response (black line, right axis) calculated by fitting to the Hawkes process.

Figure 8. The number of ‘likes’ against the exponent obtained by fitting to the Hawkes process. All of the calculated points are overlaid in one image.

as shown in figure 7. The responses become ‘bursty’ when the second part of the above equation becomes dominant. This ‘bursty’ nature became apparent after July 2013.

Interestingly, we found that the response function evolved towards the singular point where the amplitude of the feedback term diverged at $\alpha/\beta = 1$ (figure 8). The response function takes the following form [23]:

$$R(\lambda) = \frac{\lambda_0}{1 - \alpha/\beta}. \quad (3.2)$$

This phenomenon is similar to high-instability self-organization, as it increases the previous example’s flock size. In an old-fashioned way of saying it, a system evolves towards the edge of chaos [24]. An exponent distribution time evolution clearly shows how the system approaches the critical point ($n (= \alpha/\beta) = 1$) (figure 9).

(b) User’s proximity network

At this (sub)critical state ($n < 1$), it is important to determine how the user behaviour that dominates the network structure is self-organized [25]. Analogous with the previous boid swarming experiment, there could be a critical mass size at which the characteristic form of the
Figure 9. Time evolution of the distribution of the exponent ‘n’ obtained by fitting the time series of ‘likes’ events determined via the Hawkes process. The left y-axis shows the day where each distribution is calculated and the right y-axis shows the scale of the probability. The shape of the distribution gets closer to that with the exponent $n = 1$ as the service matures (from bottom to top).

network flock changes. In order to examine the correlation between the structure of the inter-user relationships and the user activities, we constructed a user network based on behavioural similarities among users by using Jensen–Shannon divergence (JSD) [26], a symmetrical version of Kullback–Leibler divergence (KLD). Using this information criterion, we calculated the users’ proximity based on the similarity of their used tag frequency, and we created a network. If the JSD value for a pair of users was less than a certain threshold value, the user similarity was sufficiently high, and the edge between them was established. The threshold value was adaptively determined in order to ensure that the total edge number was 1% of the complete graph.

As a result, the user similarity network has a typical core–periphery structure [27], and we assumed that the core part is a relatively higher order of the $k$-clique community [28]. We calculated $k$ for 3, 4 and 5, with $k = 5$ representing the core part of the network structure. It is worth noting that a relationship exists between this core–periphery structure and the creation rate of the new tag vocabularies. It seems that, due to the frequency of each user’s vocabulary creation and each user’s contribution, the total created vocabulary uses are higher for users located in higher-order cliques in the core part of the network (figures 10 and 12). The users in the peripheral parts also have the higher new tag production rate, which requires further discussion.

What emergent behaviour principle is suggested by this web services analysis? The production rate and usage frequency of the new tags seems to be higher at the higher-order cliques; in other words, it is accelerated when a group of users shares similar service use preferences. Increases in the number of similar users encourage the creation of new tags. This micro-tagging behaviour by users changes the structure of the network, which further changes the action of micro-tagging. However, this recurrent collective behaviour does not mean that the group will make rational decisions as a collective action. This picture provides new insights into collective intelligence in relation to adjacent possible theory, which will be discussed in the next section.

4. What is collective intelligence?

Collective intelligence has been defined as a collective rational action produced by a group. A typical example can be found in a rational judgement of a group of ants. In an experiment in which ants tried to build a new nest, when a fake place (decoy) was introduced, it was possible to
select an optimal location for the nest [29]. This raises the question: What divides foolish collective intelligence from clever group knowledge?

We did not analyse swarm dynamics from the collective intelligence perspective. The swarms we dealt with in this paper may not reach the optimum point in any fitness landscape. The swarm dynamics were purely kinematic. It has been shown that, when an artificial neuron model was set in each boid, flocking pattern will be developed by the evolution of the neural architectures [30]. In this experiment, a flocking pattern formation was advantageous to reach foods. In this flocking pattern evolution, we can say, in this sense, that the agents became smarter by developing groups. However, we need to further increase the total number of boids and conduct additional studies on complex task simulations to investigate if a correlation exists between collective intelligence and creating new behaviour [31].

The collective intelligence found in the large web service data analysis demonstrates spontaneous novelty production. It defines collective intelligence as something that is mediated by the web service for users to generate and maintain novelty. In addition to learning, intelligence has important elements, such as memory, perception and novel generation. Novelty refers to new patterns and structures that have never existed before. In the web service example, novelty refers to a new tag that is posted. In statistical RoomClip data analysis, the average production rate of new tags seems to follow simple statistics, e.g. Heaps’ Law. Although this production rate decreases with time, when we look at the rate at each time step, we can see that it increases sharply at a specific point in time (figure 11). We found that the new tag production comes from the user’s latent JSD network (figure 12). In the previous section, we noted that the latent user network has a core–periphery structure, where the core is a network created by users sharing similar preferences (i.e. similar usages of tag sets), and the periphery is created by singular users. When examining the new tag generation rate in the core part, we found that the rate was higher in the higher-order cliques.

Why is the new tag production rate high in the higher-clique core part? We interpreted this finding as the ability of the users to share more similar ideas (therefore, we think of it as sharing experiences). This affects the production of new tags, and it can be related to adjacent possible theory, which will be addressed in the discussion section of this paper. Because of this core–periphery network, several innovation waves—i.e. the creation of new tags—are progressively generated. It is interesting to note that the characteristic network structure is organized near the critical point, which we could infer from the Hawkes process analysis; from then on, the system becomes an innovation source near the critical point.
Figure 11. Time evolution of the number of new tags per day. At around January 2014, the tag creation rates spontaneously increased.

Figure 12. Visualization of the latent network structure using Jensen–Shannon divergence as a distance measure between a pair of users based on the frequency of their used tag vocabulary. If the JSD value for a pair of users is less than a specific threshold value, then the users’ similarity is sufficiently high, and the edge between them is established. The density in the middle is a core section of the network structure and the less connected section \((k = 1 \text{ or } 2)\) is visualized in the shape of a crescent moon under the core section. (Online version in colour.)

5. Discussion

By simply increasing the number of agents, the boid model demonstrates that new flocking behaviour occurs. In the case of the large web service data analysis, it seems that new tags are being created more frequently as the web service approaches a critical point, and it has a core and peripheral structure. Thus, as Kauffman’s adjacent possible theory [3] tells us, it is true that innovation seeds are being created. Especially in the case of the web, we noticed that people develop the ability to enhance creativity as a form of collective intelligence.
In a multicellular organism, for example, in general, each cell does not function as an individual entity if it is separated; however, once a multicellular organism is organized, it demonstrates qualitatively different functional capabilities. Even at the single cell level, we see that complicated behaviour occurs that cannot be expected from chemical reactions inside the cell. Thus, the transition from the chemical state to the life state is emergent.

These transitions are emergent and differ from self-organization or phase transition phenomena, because the structures and patterns are not final products. The transition is only an intermittent stage for the subsequent emerging stage. Adjacent possible theory insists that the previous stage produces the next stage, and the new stage is born based on the new items that were previously created. However, this does not mean that the genealogy of the cell passes anything down to the newly created items. Rather, it is understood as a ‘temporal ladder’, or a stepping stone, that will be removed after it is used to climb up that ladder. It is not used to create new items regardless of the previously created items, but the next new item is made by using the previous item as a stepping stone. The ladders used for this purpose are removed after the process is completed. The ability to create novelty is not a component of a single agency; rather, it is the product of collective agency.

When adjacent possible theory is interpreted in this way, it is possible to apply it to collective swarming dynamics. For example, in a boid simulation, because the flock’s surface curvature is different depending on the flock size, the attraction and exclusion forces for the external boids are effectively different for large flocks and small flocks. In a large flock, the behaviour of an individual flock member will be differentiated and the behavioural difference will be amplified accordingly. Small flocks have ordered behaviour, whereas large flocks have random behaviour. At the very least, larger flocks can be a source of individual behavioural differentiation, so it is possible to create a new structure evolution. The web service’s evolution is a more suitable example of adjacent possible theory. As the number of agents increases to a specific amount, a latent network is formed, and networks with higher-order cliques create novelty.

We have been advocating for the idea that massive data flow is a source of emergence; thus, it provides a concrete example of adjacent possible theory. Using massive data flow, we studied web services and parallel computing systems as examples of new innate sources [32]. The previous self-organization examples may have been too overwhelming for a very simple, nonlinear, open system. In order to create emergent phenomena, the source must be large and complex. Excessive information and material flow can become a source of innovation. The evolution of large and complex scale systems is accelerated not for statistical reasons, but by creating an adequate network structure. The evolution of a web service is a good example of this; it is a type of emergent phenomenon that is additional to real biological evolution.

Data accessibility. This article has no additional data.

Authors’ contributions. Y.H, M.O, and S.K analyzed the web data, Y.M simulated the boid experiment. T.I wrote the entire paper and took part in analyzing the web data and boid experiment.

Competing interests. We declare we have no competing interests.

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