Property of Innovation Under Different Group Size in an Open-ended Fitness Landscape: Demonstration Through Evolutionary Logical Circuits

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Keywords

Innovation, Open-ended fitness landscape, Computer simulation, Group size, Technology s-curve, Technological evolution

Abstract

Open-ended fitness landscape or architectural innovation is a key characteristic of combinatorial technological evolution. Though many have argued that this feature is important, many models were created in a closed fitness landscape. In this article, we modified a simulation by Arthur and Polak (2006) that used a computer simulation that builds logical circuits with circuits that were built in earlier trials. We used this simulation to investigate (1) whether the speed of innovation is increased by increasing group size and (2) if the nature of innovation would differ when innovation was separated by invention (new innovation that serves a purpose that never was used before) and improvement (already made innovation but is more efficient). The results indicated that indeed group size increases the speed of innovations but is limited than expected. Also, when innovation was separated with invention and improvement, the nature of the two differed. In improvement, the trajectory followed a convex function with productivity of one agent decreasing as group size increased. In invention, the trajectory showed a continuous pattern of rapid increase followed by a plateau. In sum, the results indicated that group size
does increase both innovation and improvement, but the effect diminishes as group size increase in an open-ended fitness landscape and when innovation was split, invention resembled a technology s-curve.

**Introduction**

Cultural evolutionary systems have a characteristic called open-ended fitness landscape. When an innovation in technology or a new vocabulary in language evolves, that opens up a new pathway for selection to operate. As a result, these cultural evolutionary systems tend to increase in complexity as time progress (Clark 1985; Arthur 2009; Solé et al. 2013). In the literature of technology or innovation, this is often called architectural innovation (Henderson and Clark 1990; Frenken 2006).

Many theories were created to capture the commonalities within the open-ended fitness landscape. For example, it is said that evolution in technology and language systems alike, some units (e.g. a technical element, or a word in language) is expressed more frequently than others, which creates a fat-tailed distribution (Zipf 1949; Corominas-Murtra et al. 2018). Accordingly, Arthur and Polak (2006) which specifically focused on technological evolution, has found that whenever a key invention is made, this is followed by a rapid increase in other innovations, which they called the technological Cambrian explosion. Also, newly improved innovations often rapidly replace old and less efficient innovations, which demonstrated the phenomena that was pioneered by Schumpeter (1911).

Technological innovation has also been studied in an area called cultural evolution (Mesoudi 2011; Henrich 2017). For example, Mesoudi and O’Brien (2008) showed that participants under closed fitness landscape are able to create better arrow-heads by social learning. In their experiment, participants created virtual arrow-heads that contained several dimensions (length, height, width, etc.). Using a computer program, participants could change the values of each dimension. Results of arrow-heads were given from a mathematical function that weighted each dimension with a normally distributed noise. In each phase, participants could see the results of other participants and were able to copy the arrow-heads if desired.
Experimental results showed that participants with social learning outperformed participants that could only rely on individual learning.

The open-endedness of fitness landscape and the combinatorial nature of evolution are under studied especially in technological evolution studies. This is understandable considering that open-ended fitness landscape being challenging to model, and that many models that investigate technological evolution adapt models from biology, which also models evolution as closed fitness landscape. However, as many have indicated, there are some differences between technological and biological evolution (Jacob 1977; Solé et al., 2002; Tèmkin and Eldredge, 2007; Arthur 2009; Solé et al. 2013). A bridge is needed to fill the gap between models in open-ended and closed fitness landscape.

The simplicity of the models created by the cultural evolutionists also had many implications which could be interesting to consider within open-ended fitness landscape. One such instance is the landmark paper by Henrich (2004). He proposed that increase in group size affects the uprise and the speed of cumulative technological innovations. When each agent of a group loses the cultural trait of the previous generation by some error distribution, an increase in group size can downfall the effect of this error, and in return, cumulative innovation occurs.

Whether group size will increase the speed of cumulative innovation within open-ended fitness landscape is opened for debate. Additionally, since most of the models were simplified to increase internal validity, it is difficult to measure how much that model fits with the real world (external validity). However, considering that there might be a correlation between an increase in group size and the speed of technological development in recent century within the real world, group size might act as a driver in open-ended fitness landscape. This paper aims to address this issue using computer simulation but using a real-world scenario.

In the simulation below, we modified the simulation by Arthur and Polak (2006) so that the simulation becomes similar to agent-based simulation. Agents created logical circuits that could be used in the later
trial. We added conditions where agents were able to use circuits built by other agents. This simulation is useful because the environment is open-ended and also the task is close to a task in real-life. Additionally, they differentiated innovation between invention (new innovation that serves a purpose that never was used before) and improvement (already made innovation but is more efficient) which could be useful if the two innovations evolve differently. Also, in the following simulation, agents in the same trial did not interact with one another that could create a synergetic interaction just as in Henrich (2004) for simplicity.

Method

The simulation was a modified version of Arthur and Polak (2006). In the original simulation, several NAND circuits were randomly wired together in a non-cyclic way to make a new circuit that could be used to create another circuit in the next trial. This sequence was repeated several thousand times, which created circuits that were often used in reality (e.g. OR circuit, AND circuit, and n-bit ADDER). The simulation used in this experiment added agents that created circuits simultaneously to vary group size.

In the first trial of all conditions, agent(s) started only with a NAND circuit. The agents wired several NAND circuits to create a new circuit that served a new functionality. The minimum and the maximum number of circuits that could be wired together were 2 and 12 respectively throughout all the trials. The new circuit that was created in the first trial was automatically stored in the pool, which was a group of circuits that could be used as a component for making a new circuit in the next trial. Each circuit was insured to be a directed acyclic graph. In the circuits hereafter, the choice of using which preexisting circuit was determined by a choice function (Arthur and Polak, 2006) that specifies probabilities of selection.

Circuits were evaluated by its functionality. Preceding the simulations, goals were defined which consisted of specific input-output circuitry (Table 1). When the created circuit either met the goal for the first time or was close to meeting the goal determined by the prespecified truth table, the created circuit was called invention.
Determined by the truth table, when the created circuit met the same functionality as with the circuit that is included in the pool but with less cost (here cost refers to the total number of NAND circuits used since all the created circuits are created from NAND circuits), the created circuit is called *improvement*. When improvement is made, the older circuit that fulfilled the same functionality is deleted from the pool. On the other hand, if the circuit was neither an invention or an improvement, the circuit was called *junk* and was never included in the pool.

The conditions were separated by how many agents were involved in creating the circuits in the simultaneous trial. The group sizes were 1, 2, 4, and 8. In the conditions that had multiple agents, agents created circuits by themselves. After creating the circuits, the circuits were pooled together. The pooled circuits could be used by all agents in the next trial. This means that the agents had no synergetic influence on one another.

In each condition, 1 replication consisted of 100,000 trials and 20 replications were run. Whenever all the goals were met, the replication was terminated. The program was created in GNU CLISP (ver. 2.49) which is an implementation of Common Lisp. The simulation was run on 16GB memory Windows 10.

**Results**

The number of trials by conditions and replications are shown in Table 2. Replications were terminated when all the given goals had been achieved. Trial 16 of group size 4 was aborted by memory error, thus we excluded it from the following results.

**Basic properties of evolution in group size-1**

Since the results of size-1 condition were identical to Arthur and Polak (2006), we regarded the results of the size-1 condition as a baseline. The primary results of group size-1 are shown in Figure 1.
Figure 1a shows the timing of when goals were achieved in each trial. While the trial with the fastest progress reached the 16th goal in about 30,000 trials, the trial with the slowest progress did not yet reach the 11th goal even after 100,000 trials. This indicated that a large variation existed when only 1 agent was modifying the circuits.

The number of inventions in each trial is shown in figure 1b. Generally, we see a repeated pattern where there is a rapid increase in invention followed by a period where there is minimal increase, which resembles that of a continuous convex function. This continuous sigmoidal-like pattern was present in all replication, indicating that this trend is robust.

Figure 1c shows the number of improvements that made the circuit more efficient. In total, we see a general increase in improvements as trials progress. Though in some replications we see a repeated convex-like shape in the increase in improvement, compared to invention however, the pattern is not robust.

Figure 1d shows the number of cases where neither invention nor improvement occurred. The figure indicates that there is little variance within junk. This is because the number of times innovation and improvement occurred is less than the number of trials.

**Comparison between group sizes**

Figure 2a shows the number of goals achieved in each condition with the light line indicating the actual data and the solid line the average. The average value was displayed up to a point where no termination was present in all trials. The pattern indicated that as group size increased, so did the speed of goals achieve. Likewise, the difference between conditions became larger as trials advanced. In figure 2b, light lines represent data where the speed of size-1 is increased by the number of group size compared (which also could be interpreted as dividing the number of trials in group size-1 by the number of group size
compared). Since the light line is above the solid line (which is the average of the actual data) in all conditions, this suggested that productivity of group size was lower than expected.

[INSERT FIGURE 2 HERE]

Similar to figure 2, figure 3 shows the comparison within invention. The average number of inventions indicated that as group size increased, cumulative increase in invention started to resemble that of a repetetive sigmoidal shape. This indicated that as group size increased, the gentle slope seen in replications under group size-1 was quickly followed by a rapid increase. And as quicker the goals were met, the plateau in bigger group size became longer along the end of the simulation. Figure 3b also shows when the speed of group size-1 was increased. Similar to goals, the light line is above the solid line indicating that the productivity of group size was lower than expected. We also fitted the data using OLS (ordinal least square) with the power function applied through the curve_fit function from SciPy (ver. 1.2.1) module in Python (ver. 3.6.8). Since the data fitted poorly in invention, it suggested that the increase in invention did not follow a power function and those follow a more sophisticated one.

[INSERT FIGURE 3 HERE]

Figure 4a shows the actual data and their average results from improvement in each condition. Consistent with goals and inventions, speed of improvements also increased with increase in group size similar to a gentle upward convex function. When the speed of group size-1 was increased to be compared with other group sizes, the two lines seemed to overlap with one another. This indicated that the speed of improvements was proportional to that of group size. Just as in invention, we fitted the data with OLS. The results indicated that improvement was roughly proportional to the square root times the group size, but there was a pattern in which the estimated value of the index increased as the group size increased. This suggested that as the group size increased, the rate of increase of the slope became steeper. The results from OLS also suggested that the properties of invention and improvement differed. This suggested that the nature of these two variables might be different.
Figure 5 shows the results from junk. The accumulation of junk increased as the group size increased (figure 5a). When the speed of group size-1 was increased, the results overlapped with the increased dataset. This means that productivity of junk increases proportionally to group size.

**Discussion**

Open-endedness in fitness landscape is one of the features of technological evolution. However, the nature of this aspect is under studied especially in fields like cultural evolution where many have pointed out the mechanisms that facilitate the growth in technology under a closed fitness landscape. The main goal of this study was to examine the architecture of open-ended fitness landscape through the evolution of logical circuits with varying group sizes, which is one of the mechanisms identified in cultural evolution (Henrich, 2004; Henrich, 2017).

We investigated this through a computer simulation with agents creating logical circuits using circuits that they themselves made in the past trials (Arthur and Polak, 2006). In each condition, we added agents that simultaneously created circuits. Agents in group size larger than one were able to use circuits that were created by other agents in the next trial. For simplicity, we excluded interaction between agents to see if increasing in group size alone had any effect on cumulative advancement in technological innovations.

The key results were threefold. As expected, we found that in open-ended fitness landscape, group size increased the speed of innovations. When innovation was split between invention and improvement, we found that results differed between the two. In invention, the speed that invention increased was lower than the baseline (which was the n-times the speed of group size-1) and the way that inventions accumulated were similar to a repetitive sigmoidal function. On the other hand, improvement matched
that of the baseline and the rate in which improvement increased was square root times the group size, which means that the effect of group size becomes smaller as group size becomes bigger.

One reason for the decrease in the effect of group size in improvement could be due to a chance that one of the agents in the group create an improvement so efficient that other agents could not improve any further. The chance that any agent creates an efficient circuit increase as group size increase. Additional analysis is needed to see whether such efficient circuits were made faster as group size became larger.

The interesting finding is that the function of invention and improvement differed. Especially, invention resembled a sigmoidal function, which is similar to the technology s-curve (Foster 1986; Christensen 1997; Christensen 2009). As mentioned by Arthur and Polak (2006), the rapid take-off of invention is subject to goals (e.g. AND circuit, OR circuit, etc.) being met. This means that when a goal is met, inventions using that goal circuit rapidly increase. However, at some point, the limits of using that goal circuit are reached and the growth of inventions stops. Such a result was never reported in cultural evolutionary models and can be considered as a key finding in this study. Nonetheless, since this is a post hoc analysis, whether or not the results that inventions are the same as the technology s-curve is open for debate. Additionally, the reason that this function was not seen in improvement is also an open question and needs further investigation.

Besides the difference between invention and improvement, one of the take-home messages is that even if group size increases, the productivity of one agent being added decreases as group size becomes bigger. This also suggests that an increase in group size is sufficient to maintain technology but not enough to accelerate the speed of innovations. However, we did not include synergetic interactions for simplicity in this study which means there is still room to argue that with interaction, group size does increase the speed of innovations. On the other hand, behavioral sciences have shown that group processes do not always have a positive effect (e.g. groupthink, social loafing). We need further examination to see whether interaction does increase the speed of innovations in an open-ended fitness landscape.
There are still many candidates that may affect the speed of innovations. One example is network structure (Frenken 2006; Powell et al. 1996). Derex and Boyd (2016) have reported experimentally that partial connectivity increases the innovations of a group more than a full connected group. Such mechanisms are needed to be explored in future research. So, in order to clarify the traits of innovations, not only do we need simulational studies such as this, but empirical studies that bridge between simulations and real-world phenomena.

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Author Contributions

The initial research was designed and conducted by M.S. and K.S. K.S. programmed and analyzed the data. M.S and K.S. wrote the manuscript.

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Table 1 Goals that were defined preceding the simulations.

Caption: There were 16 goals in total. N-bit adder had a range of 1 to 8.

| Name         | Inputs | Outputs |
|--------------|--------|---------|
| NOT          | 1      | 1       |
| IMPLY        | 2      | 1       |
| AND          | 2      | 1       |
| OR           | 2      | 1       |
| XOR          | 2      | 1       |
| EQUIV        | 2      | 1       |
| 3-WAY-AND    | 3      | 1       |
| FULL-ADDER   | 3      | 2       |
| \(n\)-BIT-ADDER | \(2n\) | \(n+1\) |
Table 2 The number of trials by conditions and replications.

Caption: Replications were terminated automatically when all prespecified goals were met.

| Replication | size-1 | size-2 | size-4 | size-8 |
|-------------|--------|--------|--------|--------|
| 1           | 100,000| 100,000| 95,950 | 42,000 |
| 2           | 100,000| 100,000| 58,000 | 75,216 |
| 3           | 100,000| 100,000| 100,000| 53,636 |
| 4           | 100,000| 100,000| 88,867 | 51,952 |
| 5           | 100,000| 100,000| 100,000| 38,965 |
| 6           | 100,000| 100,000| 100,000| 57,881 |
| 7           | 100,000| 97,981 | 100,000| 37,000 |
| 8           | 100,000| 100,000| 90,000 | 62,796 |
| 9           | 100,000| 100,000| 100,000| 66,986 |
| 10          | 100,000| 100,000| 68,988 | 38,100 |
| 11          | 100,000| 90,974 | 93,754 | 44,977 |
| 12          | 100,000| 100,000| 79,970 | 66,716 |
| 13          | 100,000| 100,000| 100,000| 44,000 |
| 14          | 100,000| 100,000| 100,000| 56,974 |
| 15          | 100,000| 100,000| 75,949 | 59,000 |
| 16          | 100,000| 100,000| 25,965 | 49,989 |
| 17          | 100,000| 100,000| 79,399 | 38,717 |
| 18          | 100,000| 100,000| 83,987 | 77,000 |
| 19          | 100,000| 100,000| 64,000 | 44,617 |
| 20          | 100,000| 100,000| 100,000| 46,772 |
Figure 1 The cumulative score for each variable in group size-1.

Caption: Cumulative score for each replication in group size-1
Figure 2 The cumulative score for goals in each condition.

Caption: (a) Light lines indicate raw data from each replication. Solid line indicates the average. The average value was displayed up to a point where no termination was present in all trials. (b) Solid line represents the average cumulative score. Light line represents the prediction calculated with group-size 1.
Figure 3 The cumulative score for invention in each condition.

Caption: (a) Light lines indicate raw data from each replication. Solid line indicates the average. The average value was displayed up to a point where no termination was present in all trials. (b) Solid line represents the average cumulative score. Light line represents the prediction calculated with group-size 1. (c) Solid line represents the average cumulative score. Light line represents the fitted line using power-law function.
Figure 4 The cumulative score for improvement in each condition.

Caption: (a) Light lines indicate raw data from each replication. Solid line indicates the average. The average value was displayed up to a point where no termination was present in all trials. (b) Solid line represents the average cumulative score. Light line represents the prediction calculated with group-size 1. (c) Solid line represents the average cumulative score. Light line represents the fitted line using power-law function.
Figure 5 The cumulative score for junk in each condition.

Caption: (a) Light lines indicate raw data from each replication. Solid line indicates the average. The average value was displayed up to a point where no termination was present in all trials. (b) Solid line represents the average cumulative score. Light line represents the prediction calculated with group-size 1.