DIGITAL EVOLUTIONARY MACHINES AND THEIR SPONTANEOUSLY EMERGING INTELLIGENCE

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Abstract

Intelligent operating mechanisms have so far emerged spontaneously in biology. At the beginning of life on Earth, completely ignorant beings gradually became able to understand their environment by building a knowledge base from their own experiences. In this article, we attempt to outline the above process by observing the operation of artificial beings in an artificial world. The shape of this experimental world is a torus where squared fields are on the surface. The size can be changed, and any number of beings can be launched into it. There are energy sources and energy sinks in it. The creatures require energy and thus step from field to field to get energy. At the beginning of the process, beings are ignorant. They have no experience, but remember everything that happened to them. During the simulation, we observe the progress, destruction, or rise of the creatures. We examined their knowledge base, and the boom, or extinction of groups, families, and clans. In a completely hostile world, it is impossible to survive, but in a slightly hostile or friendly world, viable populations will certainly develop, that can use their knowledge base to assert themselves. The intelligence appears always if the circumstances are not too hostile and the existing entities can remember events that happened to them. The spontaneous emergence of intelligence is not exceptional, but natural.

Keywords: spontaneous emergence of intelligence; simulation of evolution; artificial beings

1 Introduction

The evolution of living things has been researched by many evolutionary biologists for years. They are getting closer to understanding the process [1], [2] but there are still smaller details to uncover to reveal the full evolutionary process [3]. In addition to physical evolution, mental evolution is also important and complex[4], especially in the emergence of intelligence [5]. At the dawn of Earth's history, at the beginning of the evolution of life, only primitive organisms existed, which had no experience recorded in a knowledge base that could have helped their survival. They randomly drifted and wandered in the world, probably in the oceans of the world, exposed to the dangers of their environment, but also to its favorable opportunities.

More scientists attempted to describe the process where intelligence appears. There are theoretical [6–9] and experimental approaches [10–12]. The representation of knowledge is also outstanding in theoretical and experimental works too [13, 14].

Our goal is not to model life's evolution but to understand how intelligent behaviors emerged spontaneously. Our basic objective was to examine the possibilities of the appearance of intelligence in a non-living environment. Therefore, we create an artificial world into which we have introduced a large number of artificial beings (DEM workers) and observed their operations [11]. We studied different cases where workers do not learn. In this case, the wandering is probabilistic. The next case is where workers learn, store their experiences in a knowledge base, and use their knowledge to avoid known dangerous fields in the next step. The third case is where workers learn and share their knowledge with those workers who are in the same field at the same time. So If they coincide they share knowledge.

The simulation project proved that the spontaneous emergence of intelligence is possible, even realistic. This intelligence is low level like at the beginning of the Earth's history, but capable of helping its owner to survive and avoid dangers.

The simulation program package and its source code are available on GitHub: https://github.com/istvan-elek/DEM in C#.

1.1 DEM workers' skills and properties

Workers have many properties, needs, and skills that determine their operations during the simulations.

1.1.1 Workers' needs and skills

- Workers need energy to survive so they wander randomly in a labyrinth looking for energy sources
- They can step only in four directions. up, down, left, right i.e. there is no jump of more than one field
- They start their life with initial energy and an empty knowledge base
- They store every remarkable event in their knowledge base that happened to them during their 'life' such as getting or losing energy in a certain field
- Before a new step which is generated randomly, workers check if the next field is dangerous (energy sink) or promising (energy source)
- Every step requires energy. This energy is the movement cost

- If their energy has been lost they die including their knowledge base too
- If the energy content of a worker exceeds a certain value it can create offspring. New creatures are born with initial energy and parents' knowledge. Ancestors' energy decreases with offspring's initial energy

1.1.2 Workers' properties

- unique worker **ID** is for identifying individuals
- **energy** is the gathered energy collected during the activity. The energy content of a worker is fundamental for further actions, and finally for a successful existence.
- **imprint** contains the specific field positions where energy sources or sinks were found. When workers move to the next fields imprint content helps them to identify dangerous fields. This is the basis of the defensive strategy when workers know where not to go. Although imprint contains the positions of favorable fields too it will be used if the offensive strategy has been implemented. It is the next step of the research work.
- **entropy** The entropy definition is $S(B) - S(A) = \int_A^B \frac{dQ}{T}$ in physics, where S is the entropy in A and B states, dQ is the change of heat, and T is the temperature. Our definition is $\Delta sE = -|\Delta E|$, where sE is entropy, and E is energy. While workers wander and collect energy from field to field (ΔE) and their entropy changes from field to field too (ΔsE). The concept is that entropy expresses the quality of the knowledge. If knowledge-base is empty the entropy is maximum (0). The more negative the entropy value is, the more information the knowledge base contains.
- **Worker path** is the series of field coordinates the worker visited during its life.

1.2 Simulations and their characterization

Every simulation should be characterized to understand the processes. There are two ways for the analysis, first, to characterize individuals, and second, to describe the communities.

1.2.1 Individuals

Understanding the fate of a worker we used the following:

- worker's energy is the gathered energy in the current state
- worker's entropy is the entropy in the current state
- worker's path is the list of visited fields by a certain worker
- worker's imprint is a list of visited fields which visited. This list contains those fields where there are energy sources or sinks.

1.2.2 Communities

Understanding the fate of the workers' community the following parameters are available:

- population: the number of living workers is called the population
- energy ($\sum E$): it is the sum of the energy of all living workers

- entropy ($\sum sE$): it is the sum of the entropy of all living workers
- fitness (F): it is a computed parameter from the number of living workers multiplied by their energy, $F = \log \sum_i wk_i * E_i$, where wk_i is the ith worker, E_i is the ith worker's energy. Decreasing fitness predicts the extinction of the community. Increasing fitness indicates the promising future of the population.

If we are going to understand workers' fate we should investigate generations too beyond the parameters mentioned above. It is interesting how the successful clans operated.

2 The artificial world

Let us create an $N^{rows} \times N^{columns}$ sized artificial world, a labyrinth with many energy sources and sinks. Every field of this world contains some quantum of energy. DEM workers enter the fields while wandering and they reach their energy. Any labyrinth can be created with arbitrary size, energy sources, and energy sinks.

The shape of the labyrinth is not a chessboard but a torus, because the torus world has no boundaries thus wandering workers never hit walls (Figure 1).

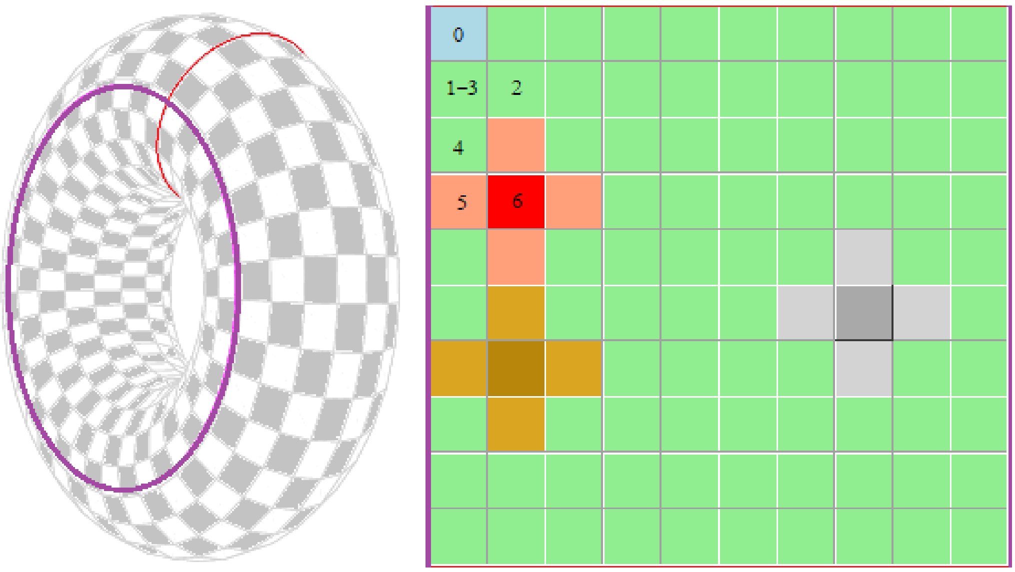

Fig. 1 The torus world (left) and its spread out surface like a chessboard (right). The red and the grey fields mean energy sinks and the goldenrod field means an energy source. The numbers in fields mean the step count of a certain DEM worker. As you can see this worker entered the red field at the sixth step and lost some of its energy.

Steps into a field of a labyrinth and the certain worker gets the energy content of the touched field, where the energy is a positive value in the case of energy source and negative if there is an energy sink in it. An empty field has negative energy which is the movement cost.

2.1 Hostile or friendly labyrinth

You can estimate the hostility of a labyrinth. Let the labyrinth size be $N^{rows} \times N^{columns}$. Its number of empty fields is $N^{rows} \times N^{columns} - N^{source} - N^{sinks}$. Let us define the static hostility that can be computed from the parameters of the labyrinth, like this:

$$H^{static} = \frac{\sum_i E^{sources} + \sum_j E^{sinks} + \sum E^{emptyfileds}}{N^{rows} N^{columns}}$$

where $\sum E^{sources}$ is the sum of energy of energy sources, $\sum E^{sinks}$ is the sum of energy of energy sinks, $\sum E^{emptyfields}$ is the sum of energy of empty fields, $N^{rows} \times N^{columns}$ is the number of fields. The H is a kind of energy density. It is a general static parameter of the world independent of the creature's position.

If $H^{static} < 0$ then the labyrinth is hostile, if it is around 0 it is neutral, and friendly otherwise. The hostility depends on not only the H^{static} parameters but the starting point too. If there is an energy sink near the starting point this worker suffers from energy loss in any labyrinth. When an energy source is near the starting point the starting worker's chance is much better. Consequently, a worker's success depends not only on the parameter H^{static} of the labyrinth but the starting position too like humans.

That's why we defined the dynamic hostility, which is the following: let us compute the distances between the starting point P_0 of a certain worker and the P_i point of energy sources (E_i^{source}) and P_j point of energy sink (E_j^{sinks}).

$$H^{dynamic} = \frac{\sum_i \frac{E_i^{source}}{{d_i}^{source}} + \sum_j \frac{E_j^{sink}}{{d_j}^{sink}}}{\sum_i \frac{1}{{d_i}^{source}} + \sum_j \frac{1}{{d_j}^{sink}}}$$

where d_i is the distance of P_0 and P_i point.

Do not forget that the movement of workers is probabilistic except for known dangers so there can be entities that avoid the dangerous fields by chance in a hostile labyrinth and can be others that reach a big energy sink in a friendly world. Neither H^{static} nor $H^{dynamic}$ do not estimate the fate of DEM workers exactly, since the problem is not deterministic.

If the start positions of initial workers are the same the scope of dynamic hostility is general i.e. it regards every worker. But if the start position is different because of the generation of random start positions for initial workers the dynamic hostility becomes individual. Later on when offspring appear their start position already depends on their birth place.

3 Workers in action

Let us launch workers into a labyrinth with the following properties and abilities:

- All important events are imprinted into their memory such as entering a specific field containing an energy source or sink in it. They store the coordinates of these fields and the field's energy content in their knowledge base.
- Before moving on they ask for a new field for the next random step. They check if the target field is dangerous. If it is not, they step on it. If it is dangerous, they ask for another random, surrounding field until they get a non-dangerous one. This is the defensive strategy. They know only where not to go.
- An initial, incomplete knowledge base can believe a dangerous field harmless, thus the destruction is massive (90-95%) at the beginning of the process. Later when the knowledge base is more developed the extinction decreases but only in the case of learning or merging knowledge.
- If the workers meet during wandering i.e. step into the same field simultaneously, they exchange knowledge. This is a coincidence.

The following will show simulations in different labyrinths with different world parameters. Three experimental circumstances were created, such as the hostile, the neutral, and the friendly labyrinths. Three worker groups were made.

First, workers do not learn, they remain ignorant during their life. Second, the case of learning when workers save every important position and event that happened to them. This knowledge helps them to avoid the energy sink fields in the further steps.

The third case is when workers learn, and merge knowledge bases if they coincide. This knowledge base is probably larger than the separate knowledge before merging. This is a more efficient tool for the struggle to survive.

The labyrinth size is set to small (100 x 100) to recognize sources (red pixels) and sinks (blue pixels) in the figures. Generally, we always use bigger labyrinths like 500 x 500 or even bigger but in this case, the pixels are too small to see them well (Figure 2).

We created three labyrinths that were hostile, neutral, and friendly. In every lab, there were many simulations with the same parameters to investigate the differences between simulations. Finally, we ran simulations when workers did not learn, learn, and merge knowledge while coinciding. These results were compared too.

3.1 Running in hostile labyrinths

Look at a hostile world there are more energy sinks than sources. In this case, workers have hardly any chance of surviving the difficulties. Some lucky workers can avoid dangers, increase their energy content, and make offspring. Our general experience is that a hostile world is neither favorable for the ignorant nor the educated. There is no chance of surviving and forming a prosperous population. A hostile labyrinth can be seen in Figure 2.

3.1.1 Not learning workers

In this case, workers wander randomly in this world. They do not learn and do not save experiences. Their knowledge bases are empty. Since their moves are probabilistic they have very little chance of finding energy sources (Figure 3). It is unlikely but not impossible thus it can be such cases when they reach energy sources and even produce

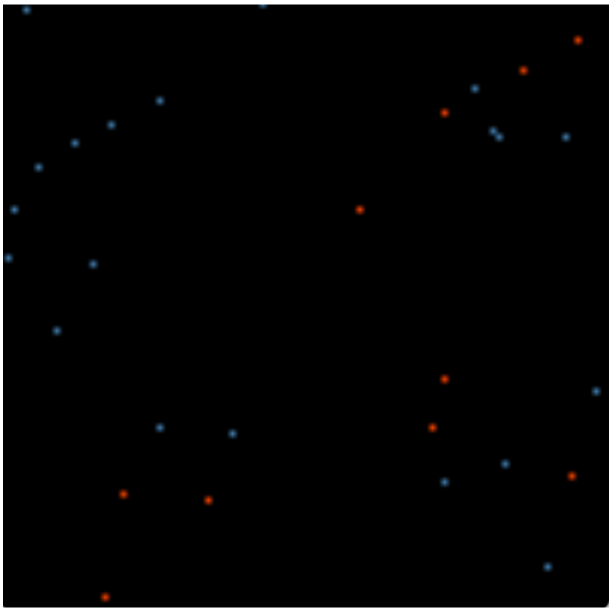

Fig. 2 This is a hostile labyrinth where the lab size is 100 x 100 i.e. 10,000 fields. The number of energy sources is 10, and the number of sinks is 20

offspring. In some rare cases, developing populations appear from ignorant workers. But the typical scenario is that ignorant workers die out in a hostile world.

3.1.2 Learning workers

Even though workers learn, their chances of survival are not good because there are not enough available energy sources. In exceptional cases, they can survive and even create a large population, but the probability is low. Based on the study of many cases it can be claimed that they generally survive longer than their not learning peers (Figure 4).

3.1.3 Learning and merging knowledge

Regarding the hostility of this world, the learning and merging workers there is hardly any chance of creating a large population. In lucky cases, if some workers reach enough energy sources, there can be a large population (Figure 4). We generally claim that the appearance of a large population is unlikely but possible in a hostile world.

3.2 Running in neutral labyrinths

A neutral labyrinth means the number of energy sources and sinks are the same, and the labyrinth's size is not extremely big. When wandering workers can catch enough energy sources, especially if they learn, or merge their knowledge when coinciding. The difference between the case of not learning and learning can be remarkable. A neutral labyrinth can be seen in Figure 5.

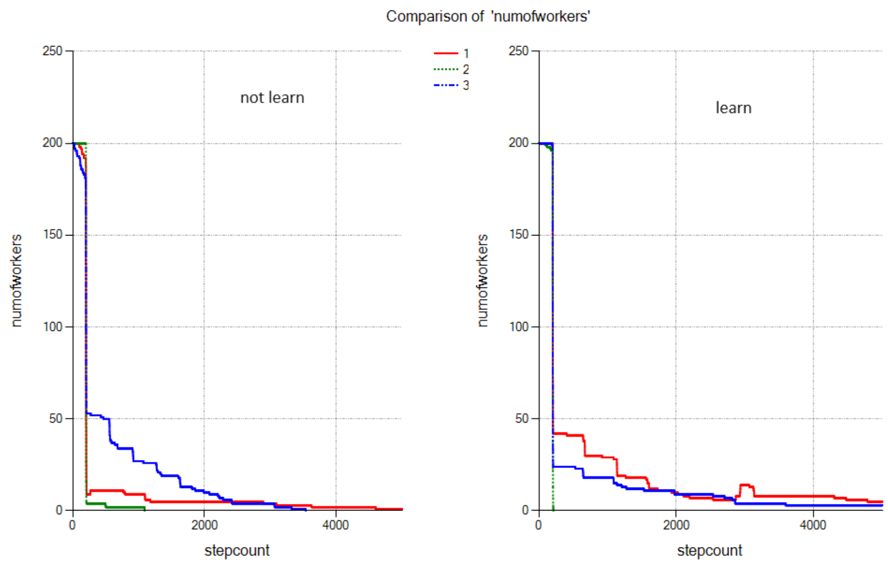

Fig. 3 Comparison of populations in different runs on the labyrinth (Figure 2) where workers did not learn (left side of figure). As it can be seen all workers have died in all simulations. The right side of this figure shows the case of learning. In both cases, all workers have died in all simulations. It is not surprising because generally, it is almost impossible to survive in a hostile world. An interesting experience was that learning workers died later than not learning peers

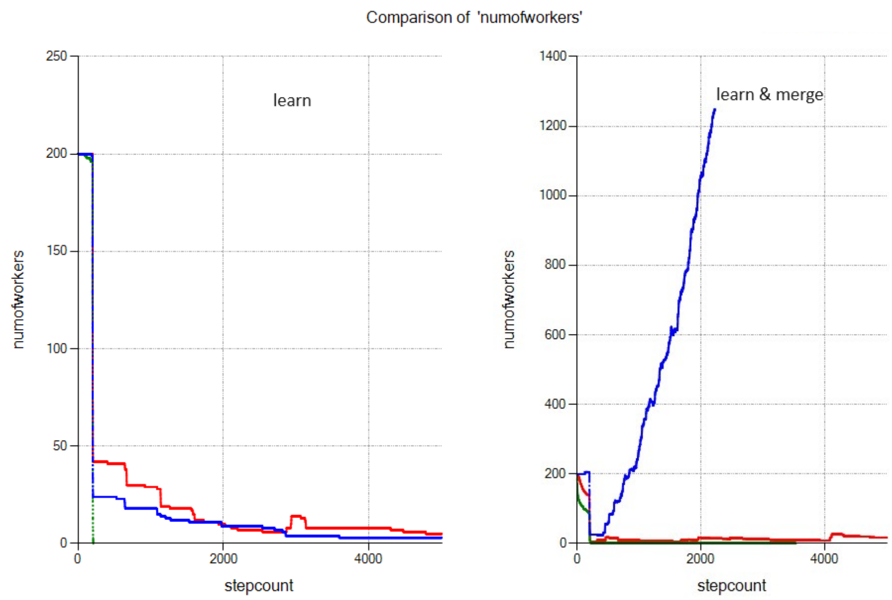

Fig. 4 Comparison of populations in different runs on the labyrinth (Figure 2). Three curves show the population of different runs when workers learn (left side) and merge knowledge (right side). Almost all workers have died in all simulations except in one merging case. It is not surprising because, generally it is almost impossible to survive in a hostile world. There can be lucky workers who exceptionally survive and make a large population but it is rare

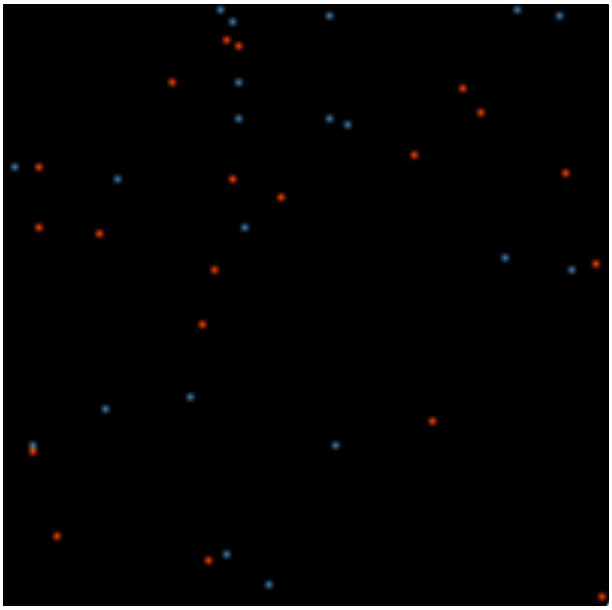

Fig. 5 This is a neutral labyrinth where the lab size is 100 x 100, the number of energy sources is 20, and the number of sinks is 20

3.2.1 Not learning workers

Let us look at a neutral labyrinth where the number of energy sources and sinks are the same. Although workers are ignorant and the labyrinth is not hostile they have more chance to be alive and create a large population (Figure 6).

3.2.2 Learning workers

The learning workers have a big benefit versus not learning peers because they can avoid the known dangers coming from their knowledge. Although no-learning workers have a good chance of surviving too, the learning peers have more chance to create a large population (Figure 6).

3.2.3 Learning and merging knowledge

The learning and knowledge-merging workers have the biggest chance for a high life. They can create a large population and their offspring start their life with useful knowledge of the surrounding world that enhances their chance (Figure 7).

3.3 Running in friendly labyrinths

Look at a friendly labyrinth there are more energy sources as sinks. There is an interesting experience in a friendly world. Every worker has a good chance to survive since energy is available in enough quantity in the labyrinth. There can be a big

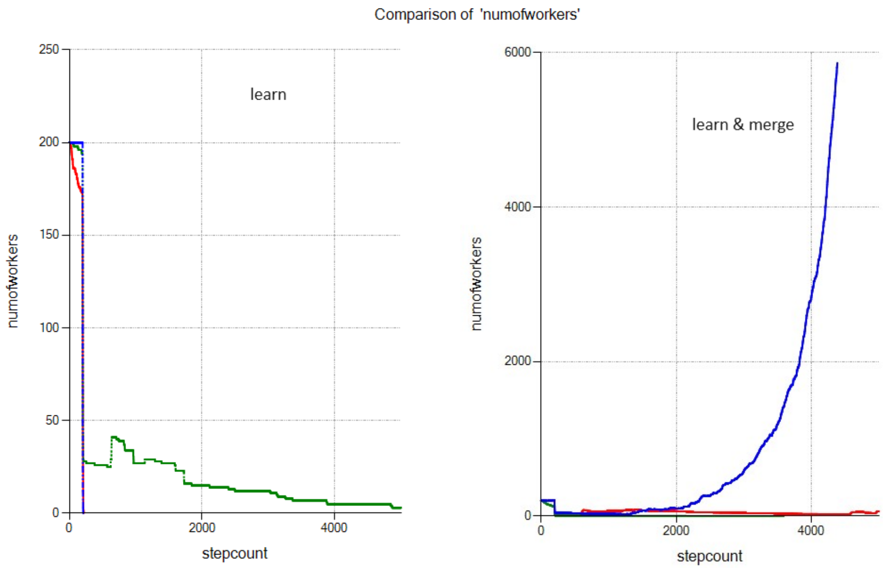

Fig. 6 This is a comparison of the population of a simulation on a neutral labyrinth with no learning (left side) and learning (right side

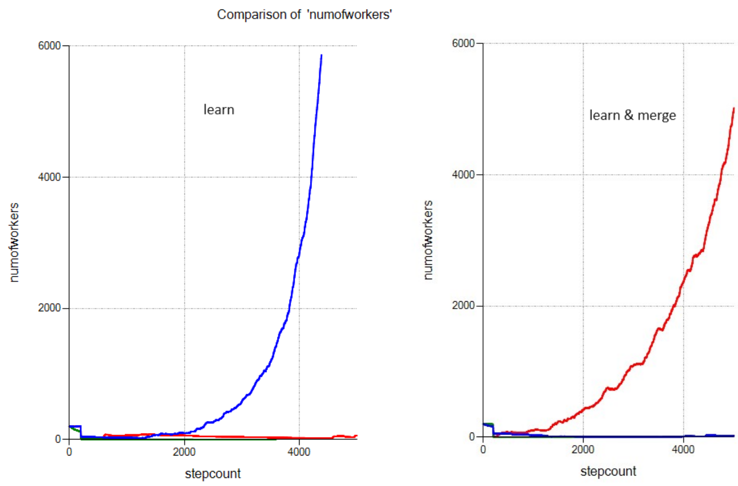

Fig. 7 This is a comparison of the population of a simulation on a neutral labyrinth with learning (left side) and merging (right side)

difference between the learning and not learning cases. The learning and knowledge-merging entities have a significantly better chance of creating a large population. Our general experience is that a friendly world is a comfortable nest for every entity.

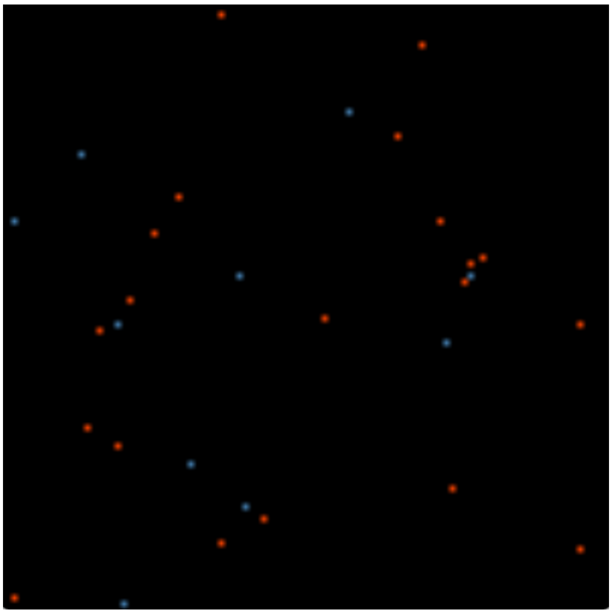

Fig. 8 This is a friendly labyrinth where the lab size is 100 x 100, the number of energy sources is 20, and the number of sinks is 10

3.3.1 Not learning workers

Look at a friendly labyrinth there are more energy sources and sinks. Although workers are ignorant and the labyrinth is friendly, they have more chance to be alive and produce a remarkable population (Figure 9). In a friendly world, the knowledge base is not necessary to have a promising future but is useful.

3.3.2 Learning workers

Learning always provides a better chance for a productive life. The knowledge base, if it is large enough, is a guarantee for prosperity (Figure 9).

3.3.3 Learning and merging knowledge

Learning and merging knowledge always provide a better chance for a community to have a prosperous future. A high-level knowledge base, if large enough, guarantees the booms of a society (Figure 10).

3.4 Comparison of learning, and merging cases

Now let us compare runs in neutral and friendly labyrinths when workers do not learn, learn, and merge knowledge (Figure 11). Learning, learning, and merging knowledge is always useful for workers. Although ignorant workers can be alive in a friendly world learning peers' prosperity is better since their energy is much higher in most cases. Do not forget that fortune can disturb this tendency.

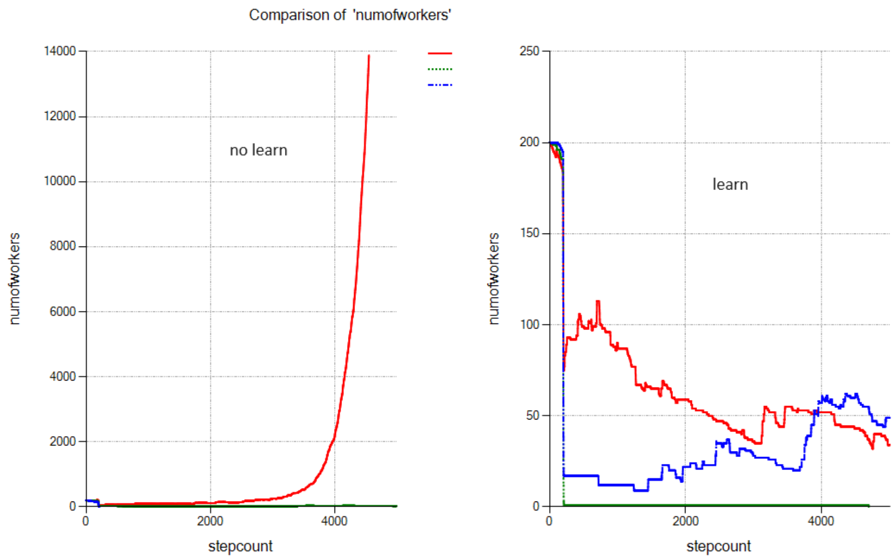

Fig. 9 In this figure, we can see the result of the simulation where workers do not learn (left side) and learn (right side)

3.5 Energy, entropy, fitness, worker path

Until now we demonstrated the course of the processes of the different scenarios with population. Other parameters such as energy, entropy, and fitness also provide a proper description. Now look at them in Figure 12.

Since workers live as long as they have enough energy it is suggested to investigate their energy content. To live and replicate requires energy as it was mentioned above.

Entropy is a good parameter to compare the populations' knowledge but also good to compare individuals' knowledge. Although imprints contain dangerous and prosperous points to compare them, it is better to use entropy. If a worker has larger entropy than another, its knowledge is larger too.

Fitness is an additional parameter to describe a population. It is generated by the number of the population multiplied by its energy content. Fitness is a more complex parameter than the number of the population because a large population with low energy is less prosperous than where the same size population has larger energy. Larger fitness predicts more chances to live and develop.

A further promising parameter is the worker path. It contains the visited points with their energy content. Both individual workers and a community can be characterized by the worker path (Figure 13). Since the workers' paths in a community are the union of individual worker paths there is a big difference between them.

Figure 14 shows the difference between a few times and frequently visited fields.

3.6 Generations and clans

The role of different generations can be interesting during the analysis of the simulation results. It is important to understand the fate of successful clans. Why do they have

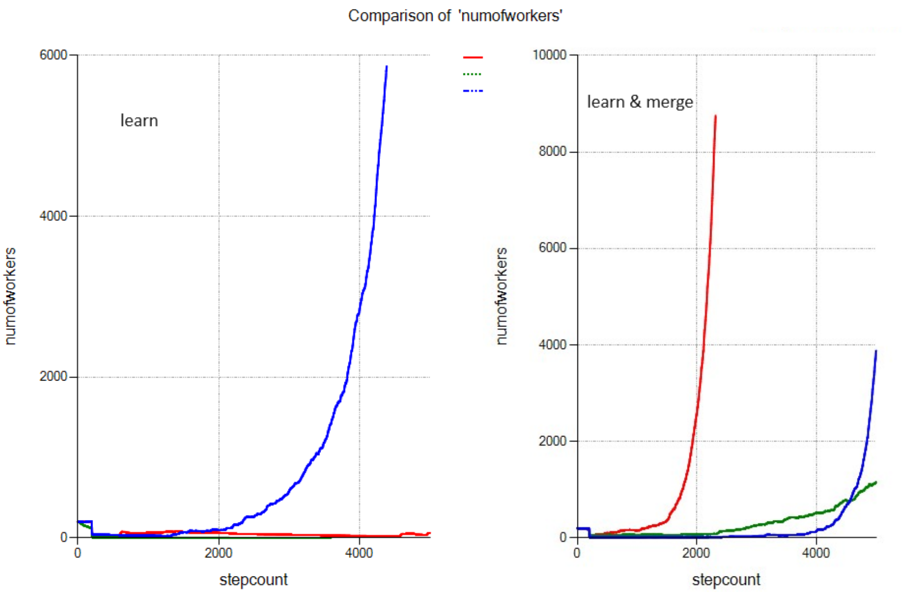

Fig. 10 In this figure, we can see the result of the simulation where workers do learn (left side) and merge their knowledge if they coincide (right side)

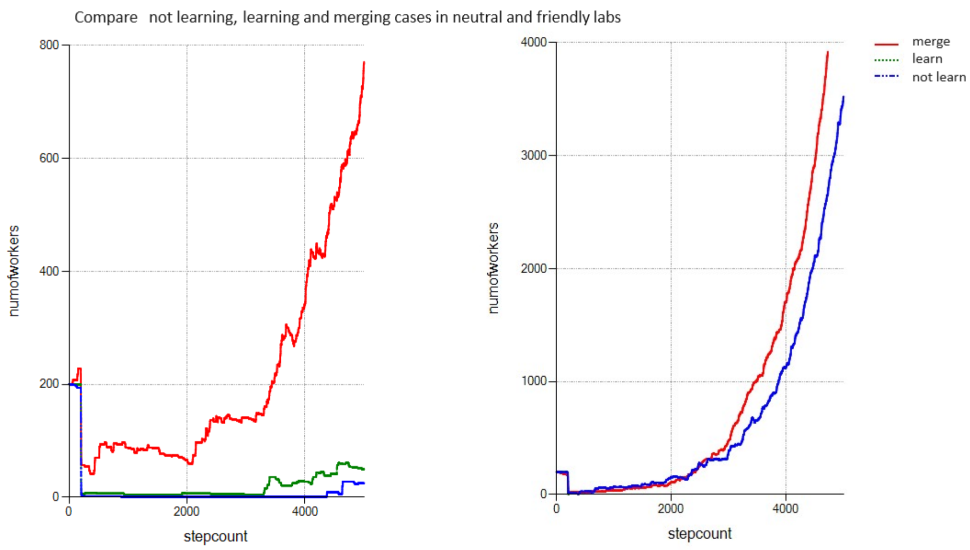

Fig. 11 This figure shows simulations in neutral and friendly labyrinths where workers do not learn (blue line), learn (green line), and merge their knowledge (red line)

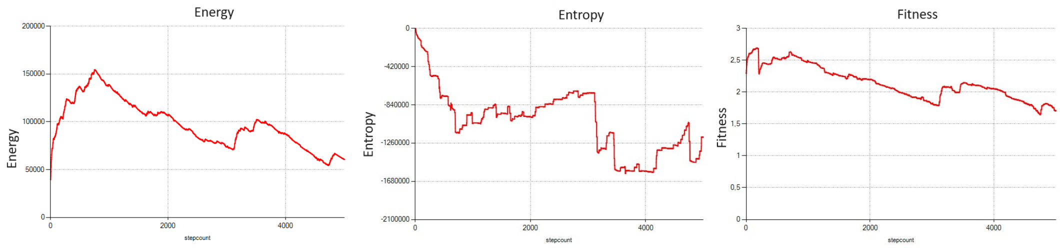

Fig. 12 This figure shows the energy (left side), entropy (middle side), and fitness (right side) of a collapsing population. Since workers' energy is an essential condition for the existence and the replication the energy content of a population indicates the prosperity of a society. As we introduced previously, the smaller the entropy of a population is, the larger its knowledge. Fitness is the product number of population $\times$ its energy thus this parameter indicates the prosperity of a society. Monotone decreasing fitness predicts extinction, on the other hand, the increasing one the long-term prosperity. The Y-axis is logarithmic since the range of fitness value is very wide

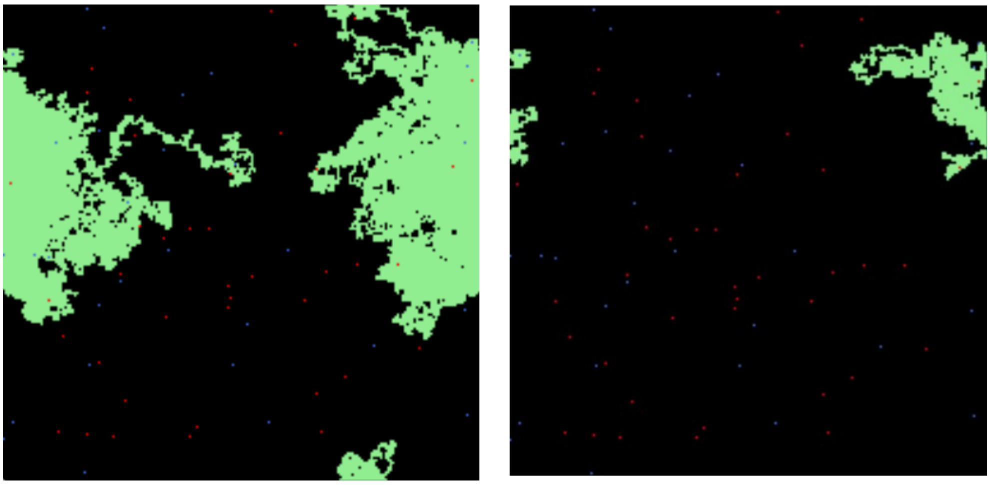

Fig. 13 This figure contains the worker path of a community (left side) and an individual one (right side). The green pixels represent the visited points and the black points are the intact fields of a labyrinth

many offspring? What did they do well? Look at Figure 15, 16 where we can see family trees and clans in graphic form.

To draw a family tree for workers is a hard task. There are many living workers, who are ancestors or offspring. That's why we do not display a traditional family tree. The ancestors are in tree nodes, which can expand or collapse. Another display type is where the living workers are in the leaves of the tree on top and ancestors are hanging on them(Figure 15, 16). Since there are a lot of workers displaying all workers in a paper is impossible. By magnification and scrolling all the workers can be seen.

Clans and big families are seen with a cumulative figure where big circles symbolize clans with their IDs, and the number of clan members below IDs.

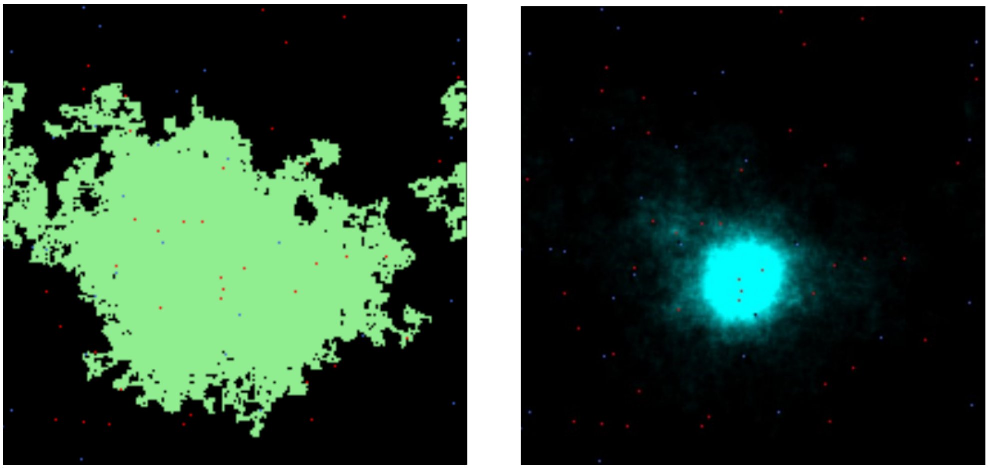

Fig. 14 The left side of this figure shows the visited fields. Green pixels mean one or more times visited fields. The right side shows pixels with different intensities. The intensity symbolizes the frequency of the visitation. The brighter a pixel is, the more workers have been there

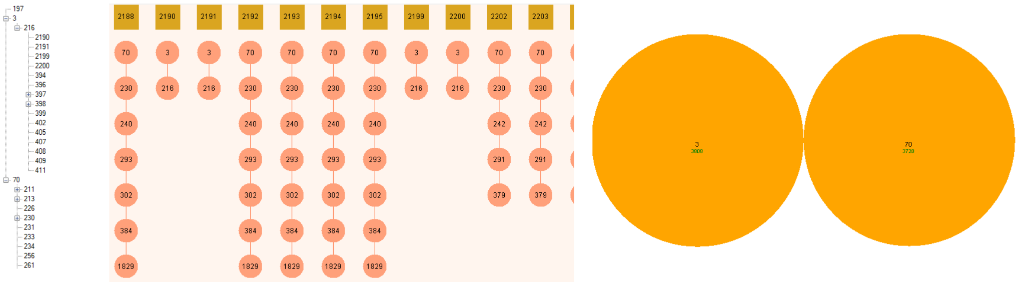

Fig. 15 Family trees and clans can be seen in this figure. Living entities are in the leaves (goldenrod squares), and ancestors symbolized by orange circles are hanging on them.

4 Conclusions

Our main claims are based on simulations with different run and labyrinth parameters.

1. There is no chance of survival in a hostile world
2. There is little chance of survival in an indifferent or somewhat hostile world without learning
3. There is a good chance that you will prosper by learning and combining knowledge
4. There is a chance to survive even without learning in a friendly world
5. In a friendly world, entities with a knowledge base capable of representing their interests always emerge
6. By learning and combining knowledge, there is a good chance of prosperity, a population can rise up

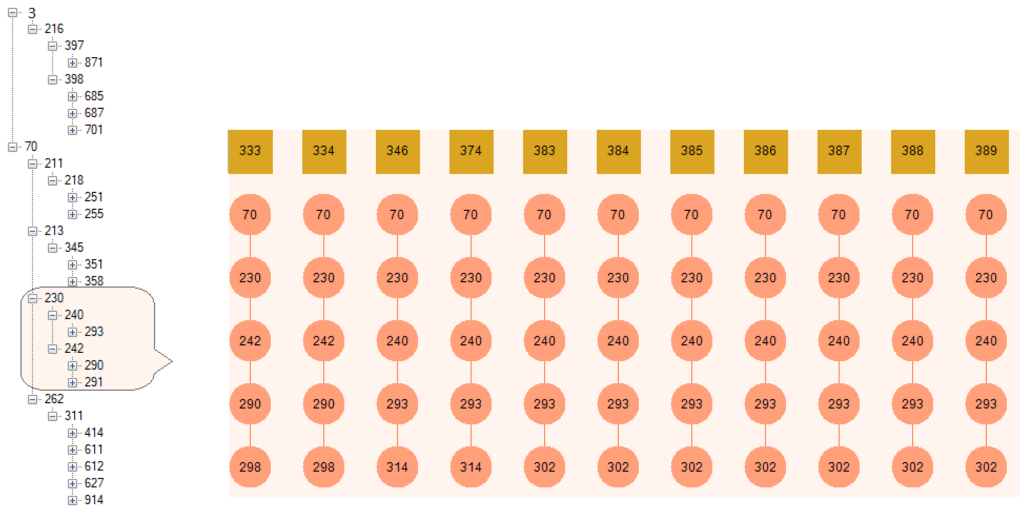

Fig. 16 This is the fifth generation family tree. Leaves contain the living workers (goldenrod squares), and their hanging ancestors (orange circles)

7. Although the intelligence formed in this way is individual and bound to the individual, the result is still a collective product. If they did not exist in multitudes, it would be quite unlikely for a single entity to become intelligent
8. A defensive strategy is not enough for the development of higher intelligence
9. The intelligence always appears if creatures remember everything that happened to them during their operation and can rely on this experience when needed

5 Future

Where are we now? Are we already where an earthworm is? No, not yet, but we are close.

1. Modeling disasters: dinosaurs appeared 230 million years ago and became extinct 65.5 million years ago. After the cosmic disaster, their knowledge base could not save them. The changed circumstances require a new, modified knowledge base. We plan to model the effect of changing the labyrinth when energy sources become unreachable for some next iteration steps if somebody enters this field and eats its energy content.
2. Offensive strategy: workers should know where the dangerous fields are which are prohibited (defensive strategy), and where to go while searching for an energy field. This knowledge base requires a more developed logic [15]. For creating a graph structure every needed data is available right now. Graph nodes are the imprint parameter and edges derive from workers' paths. This database will be an advisor, that helps workers find the most advantageous position of the next step.

3. The other worker can also be a source of energy. It is a kind of predatory lifestyle. Although our aim is not to simulate biology, it can be interesting in practical applications.
4. Allowing individual forms of behavior, such as one exchanging knowledge, and the other not
5. Let's look for practical applications: e.g. let's examine whether it is possible to fill the labyrinth with something else, such as with the objects of banking, economy, or warfare, and adjust the workers' functions accordingly. Let's examine the most successful workers and populations to see how they achieved their success.

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