Making sense of nonsense: Evolutionary Emergence of Perceptual Assimilation of Environment in Agent Based System

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Abstract

The abilities of organisms to discern, categorize and act on external cues are very sophisticated and are based on a number of underlying processes. To investigate the development of these abilities, we designed a new evolutionary agent-based system where agents start with no executable functions nor with the inherent ability to recognize other elements in their environment. Instead, the agents can only perceive externally visible properties (phenotype) of other agents initially. Over the course of evolution they gradually construct their own reactions to perceived properties. To minimize constraints on the building of adaptations, the only measure of success in our model is the agents’ ability to survive and reproduce. To survive, agents need to collect energy by learning to recognize and feed on either other agents or on “primary food”. We ran a series of experimental runs where we compared evolutionary development of agents between two settings: \( s^+ \) where agents are allowed to develop awareness of their environment and \( s^- \) where they are completely ignorant of it. In the case of \( s^+ \) evolution, the system settled on cyclic interdependent swings between a large number of prey and much smaller number of predators, as in real ecological systems. Our results show that in \( s^+ \) setting, the agent’s early evolutionary focus is to, as soon as possible, expand their ability to perceptively assimilate environment and to functionally categorize environment by developing a variety of adaptive responses to newly assimilated environmental properties.

Introduction

To instinctively discern, categorize and act on external cues all modern organisms rely on a number of sophisticated underlying processes. The question is how, during evolution, an arbitrary property of the environment became a proper signal that triggers a set of adaptive actions. For example, imagine an alien organism dropped onto Earth with just a limited reservoir of energy. To survive, it would need to (i) extremely rapidly scan and try to categorize an initially non-sensical environment, and at the same time to (ii) frantically start reconfiguring and rebuilding itself to accommodate to this environment. Eventually, if it survives, it will build a sufficiently useful representation of a slice of Earth’s environment. Based on that representation it will discriminate what appears to it as food, dangers, obstacles and will act according to such internal categorization. Will its representation be significantly different from those of earthly creatures? It depends on a lot of factors, but according to the current consensus in the scientific community, perception does not need to faithfully mirror any subset of reality, but relationships among perceptions should reflect relationships among aspects of reality (Mark et al., 2010). In other words, what our hypothetical organism perceives should be a good enough approximation of reality in order for it to survive.

The ability to develop adaptive reactions based on novel perceptive inputs through evolution is a universal property of living systems. Newly developed mechanisms can be relatively niche specific (Good et al., 2017; Long et al., 2018) or they can change the evolutionary trajectory of life on our planet, like the evolution of light and oxygen sensing in photosynthetic eucaryotes (Rockwell et al., 2014). In any of these cases, organisms had to deal with evolutionary novelities by either incorporating newly perceived environmental property into an existing functional trait (Gould and Vrba, 1982; Taylor and Raes, 2004) or by creating entirely novel functional combinations (Patthy, 1999; True and Carroll, 2002). However, only recently the tools required to explore the mechanistic basis of innovation have been developed and applied to the study of evolutionary novelties (Wagner and Lynch, 2012). Therefore, the field is still young and crowded with a number of open debates. For example, in the debate on evolutionary contingency, the question is whether evolutionary outcomes are fundamentally contingent, unpredictable and path dependent, or evolution would always lead to a limited set of outcomes (Blount, 2016). Another debate is around the question of the extent evolutionary fixation of randomly introduced novelties is constrained by existing physiological structures (Gibson and Wagner, 2000; Waddington, 1942). These debates have major implications on understanding the degree in which history influences evolutionary dynamics of biological systems (Desjardins, 2011). However, since the only available evidence for any of these debates stems from tracking evolutionary history of existing, already well formed organisms, it would be exceedingly hard to find any generalized conclusion. For example,
introduction of viable evolutionary novelty into an organism is by default constrained by its existing organization. Therefore, there is no way we can objectively and definitively generalize how constraints develop over time and how they correlate with the complexity of the organism.

To investigate such early evolution we designed a new evolutionary agent-based system where agents start at a blank slate: with no executable functions nor with the inherent ability to recognize and act upon other elements in their environment. Their inability to recognize elements of the environment is a simple consequence of the initial lack of mechanisms for discerning, categorizing or acting on external cues. Instead, the agents initially can only perceive externally visible properties (phenotype) of other agents. Only during evolution they gradually construct their own reactions to perceived properties. For the evolutionary process of incorporating perceived properties into a sequence of actions, we will use the term assimilation. Within the similar context, the term assimilation was introduced by Jean Piaget (Piaget [1974]). In his work, assimilation refers only to the process of fitting observed information into already existing functional structures. In our model however, two processes will take place simultaneously: building of sequences of actions (in the form of decision trees - see Model Description below) and incorporation of perceived elements of environment into those sequences. Therefore, we can state that our goal is to understand the evolutionary transformations of mere external properties into meaningful signals, and of disjointed actions into purposeful functions.

Since we want to observe the very process of formation of functions we will not constrain evolution by imposing any form of predefined fitness function. In common applications of evolutionary computation, fitness function defines the desired aim of the evolution and each evolutionary change is measured against that aim (De Jong [2006]). It radically increases the efficiency of the algorithm but at the same time puts sharp constraints on the adaptive structures that could emerge during the evolution. Therefore, to minimize constraints on evolutionary development of adaptations, the only measure of success in our model are the agents’ ability to survive and reproduce, which in turn depends on efficacy and efficiency of internally developed functioning.

The similar strategy has been applied in several Artificial Life computational platforms, like Avida (Lenski et al. 2003; Ofria and Wilke, 2006) or Geb (Channon, 2006). They also do not have explicitly defined fitness function and the agents in them first need to build proper procedure in order to absorb resources (Avida) or attack and reproduce (Geb). However, the crucial difference between our model and the existing ones is the ability of our agents to evolutionarily develop categorization of external inputs. Whether something will be considered food, obstacle or to be completely ignored is up to the subjective perspective of agents. Although there is a number of theoretical analyses of such minimal...
tes how many elementary actions they can execute at each time step, while nutrition value and health have the same function as in non-evolvable agents. The only difference is that the health value is larger than 0 and can be reduced during their lifetime (see below point 4 - description of attack action). However, in contrast to non-evolvable agents, evolvable ones can mutate, perform actions and perceive the world around them (Fig 2) using the set of pre-built elementary actions. However, this set of elementary actions is latent at first. It means that the agent cannot execute them until they are incorporated into the internal networks of actions, which are in turn gradually built during mutations (see the next paragraph). Therefore, the agents do not have pre-defined rules for the timing and the order of execution of those actions, nor are they equipped with build-in mechanisms of how to respond to perceived external data.

Mutations are activated at each time step. For each agent, the algorithm randomly chose whether they will mutate attack strength, speed, the internal network of actions or nothing (probabilities are given in the table). Network mutations are further divided into the following possibilities: creation of a new tree, deletion of an existing tree, node addition, node mutation and edge mutation. The networks are gradually formed via node addition when elementary action is randomly picked and either used as a starting node of a new network of actions or added to an existing network. Networks are formed as directed rooted trees where the first added node is the root and all edges point away from it (see Fig 2). Each edge has a randomly defined mutable weight, while edges that stem from a sense node have an additional attribute which defines observable distance to which sense can be applied. Both of these attributes are mutable and they are targeted under the “edge mutation” branch.

The set of elementary actions, which are the source for building internal networks, have six elements: move, eat, reproduce, attack, sense, and self-monitoring:

1. **Move** gives them the ability to change positions from one grid cell to an adjacent one. Movement is further divided into three possible ways: random, towards (an arbitrary target) and away (from an arbitrary target);

2. **Eat** can be executed only when the acting agent and the target agent are in the same grid cell and if the health of the target agent is zero. So, if an agent encounters primary food, it can eat it immediately since the health of the primary food is fixed at zero;

3. **Reproduction** asexually produces a single offspring per activation. Since it is an asexual reproduction, there is only one parent and there are no “gene” shuffling procedures. Energy cost for the parent agent (the one who executes reproduction action) is a fixed value of its energy. The newly created agent inherits all properties of the parent and is placed in a randomly chosen adjacent cell. Reproduction cannot be executed in two cases: if the parent does not have enough energy or if all 8 neighboring spatial cells are occupied by other evolvable agents;

4. As eat, **attack** can be applied only to agents that are in the same spatial cell. When executed, it reduces the health value of the target agent by the value of the attack strength of the attacker. Attack strength is a mutable characteristic so it can evolve through time;

5. **Sense** is an action by which an agent perceives one observable external property from the environment and connects it to some randomly chosen elementary action. For example, if during mutation **sense** is chosen, it will first seek all observable properties within a defined radius around the agent, randomly pick up one (if there is something within the radius), and connect it with a randomly chosen elementary action. When node **sense** get integrated into a tree, the chosen external property is stored as an attribute of that **sense** node. As a result, introduction of **sense** during mutations can either produce no change (if there is nothing observable within radius) or will add a
new branch to the existing tree, made of two nodes: sense and action. Further, with each activation of the path that contains node sense, that node will, in the visible environment, search only for the external property stored as its own attribute;

6. Self-monitoring is similar to sense, but in this case it collects internal data that belongs to the agent itself (e.g. its health or energy level).

During the execution steps, each agent should determine how it will behave. Its behaviour is determined by paths that could be extracted from its internal trees. First step is to extract all shortest directed paths that start from the root node (see Fig. 2h) of each internal tree. We used Dijkstra’s algorithm for the shortest paths as found in python package NetworkX (Hagberg et al., 2008). All obtained paths are then sorted according to their total edge-weight. The only paths executed are the highest-weighted ones whose total number of nodes is up to the agent’s speed value. If the paths include sense or self-monitoring nodes, downstream nodes can be activated only if the target of sense is actually perceived. In the given example (Fig. 2h), activation of path No. 6 will lead to the following sequence of actions: attempt to eat, sense external property, move towards it, attack the agent to whom the perceived property belongs.

All simulation parameters are in Table 1. As emphasized in the introduction, explicitly defined fitness function does not exist. Instead, the only guiding force of the evolution is reproductive success.

**Evolutionary Emergence of Functional Diversification**

In all experimental runs we compared models with and without the sense action, where the agents are either aware of their environment or completely ignorant of it. If the agents are ignorant of the environment, they can randomly move and eat without the abilities to discriminate parameters in their environment and to perform actions as a response to environmental signals. Then, the model with ignorant agents can serve as a control against which we measure relative importance of the sense action. Experimental settings will be labeled: $s^+$ (with sense action) and $s^-$ (without sense action). In both settings, we labeled agents as neutral when they ate other evolvable agents as well as non-evolvable agents approximately evenly ($\pm 10\%$ difference) during the last 5 generations. Predators are those who ate only other evolvable agents, while prey are those who fed only on non-evolvable agents, both during the same time period.

In $s^-$ settings, simulation results can be summarized in a few main findings: (i) absolute dominance of the number of prey agents from the very first evolutionary steps (Fig. 3h), (ii) no significant correlations between attributes of agents that belong to the same subpopulation (predators, prey, neutral) (iii) no significant correlations between any attributes of predators with those of prey agents and (iv) significant increase in a number of decision trees and their complexity (Fig. 4). Sharp distribution of the number of agents per subpopulation is expected because the ability to feed on non-evolvable agents (and thus be labeled as prey) does not require evolutionary development of any complex internal mechanisms: there are no preconditions in order to eat non-evolvable agents (i.e. they do not need to be killed) and non-evolvable agents occupy 87.5% of all cells (i.e. food is abundant enough that random foraging is affordable).

However, when the sense action is introduced into evolution, results become significantly different, on both population and individual levels. At the individual level two differences from $s^-$ stands out. The first one is the much higher rate of initial evolution of agents (Fig. 4), measured as a slope of linear interpolations of parameter values over the first 300 generations. In the $s^+$ settings, rate of evolution of the (i) number of decision trees, (ii) size of decision trees and (iii) speed are 8.75, 2.6 and 7 times higher respectively, than in $s^-$. Attack strength degrades gently in $s^-$, compared to the gently increasing trend in $s^+$. The second important difference is the emergence of correlations between attributes of agents within the same subpopulation. Within the $s^+$ predators, the average correlation after 10,000 generations, between attack and speed is $+0.68 \ (p < 0.001)$. For the $s^+$ prey, correlation between the same attributes is much weaker ($0.25, \ p < 0.001$). At the same time, there are no significant correlations between any of attributes, either within

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<td>probability of not mutating in the time step</td>
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Table 1: Parameters of simulation
or between any of $s^{-}$ subpopulations. In nature, correlated evolution is expected for functionally coupled traits, whose individual performances depend on their mutual interactions (Márquez and Knowles 2007). Therefore, correlated evolution of agents’ properties within the subpopulation of predators in our model strongly indicate the emergence of functional integration.

Similarly to $s^{-}$ evolution, during $s^{+}$ evolution there is a clear separation into three subpopulations, (Fig. 3b) but it happens much later, after the first 2,000 generations. After that initial period, when the clear distinction between subpopulations is established, number of predators and prey became strongly negatively correlated ($= -0.89, p < 0.001$) over the next 8,000 generations. During that time, the health level of prey became negatively correlated with speed and attack of predators ($-0.68$ and $-0.67$ respectively, with $p < 0.001$ for both). This could be explained as an indicator of establishing interdependent ecological balance between two major subpopulations.

As an additional reference point for $s^{+}$, we can use the first 2,000 generations, when subpopulations are still in initial turmoil. During that time correlation between health of prey and speed and attack of predators is $-0.19$ and $+0.28$ ($p < 0.001$), respectively. During the same time interval, there are no significant correlations between attack and speed in both predators and prey subpopulations.

Interestingly, the average attack is almost the same for both predators and prey (3.36 and 3.28, respectively), but the standard deviation for prey subpopulation is 2 times higher than for predators (2.15, and 1.05, respectively). At the same time, the average speed of predators is 11% higher with the same standard deviation ratio (1.2 for predators vs. 2.3 for prey). So, fluctuations of values of attributes in predators are much lower than in prey agents.

Since there are no fitness functions, it is interesting to identify where the strongest selective pressure is. We tracked all evolvable characteristics of agents and measured the extent of divergence of their evolutionary fixed values from the random walk during the first 300 generations (see inset to Fig 5). We chose the first 300 generations because it is the period when during the simulations, the fastest evolutionary changes take place. For all examined characteristics, the upward trend is at place in both $s^{+}$ and $s^{-}$. The average number of decision trees per agent exhibit the strongest growth by far, even though the mutation probabilities of adding a new decision tree and deleting an existing one is the same. Analysis per subpopulation shows that increasing trend of the number of decision trees in $s^{+}$ is the highest in predators, followed by prey and neutral agents (Fig 5). Average growth rate in $s^{+}$ is 4 times higher than in $s^{-}$, for the first

Figure 3: Number of agents during the typical run a) without sense action and b) with sense action. To smooth out high fluctuations in b), all lines represents 100-step moving average.

Figure 4: Average evolutionary speed of agents’ properties over the first 300 generations. Bars represent values of slopes of linear interpolations for indicated attributes. Linear interpolations are calculated for all agents, no matter how they are tagged.
Figure 5: Average number of decision trees in different subpopulation of $s^+$ evolvable agents. The graph is the snapshot of the first 300 generations when the strong growing trend takes place. Linear trendlines are in the same colour as bars of the subpopulations. Although polynomial interpolation fits the available data much better, we used linear approximation to better emphasize growing trend. Linear slopes are $0.072$ (predators), $0.046$ (prey) and $0.05$ (neutral). Inset graph shows slopes of linear trend lines for the number of decision trees (slope $m = 5.6 \times 10^{-2}$), size of the decision trees ($m = 1.3 \times 10^{-3}$), attack ($m = 9 \times 10^{-4}$) and speed ($m = 7 \times 10^{-4}$) in predators. All are calculated for the first 300 generations.

300 generations. After that initial period of rapid growth, the average number of $s^+$ decision trees per agent stabilizes and starts to fluctuate around 28 for predators, 21 for prey and 6 for neutral agents. In $s^-$ the average number of decision trees for prey and neutral agents reaches similar levels as in $s^+$. The only exception are $s^-$ predators where the average number is 14 which is half of the number of trees in $s^+$ predators.

On the other hand, growth of the complexity of decision trees (measured as the average number of elementary actions per decision tree) reaches a dynamically stable state much earlier. For the complexity, most of the growth happens during the first 100 generations. During that time, the slope of the average growth rate of $s^+$ complexity of decision trees is 0.019 which is still approximately 6 times lower than the growth rate of the $s^+$ number of decision trees (slope $m = 0.113$) for the same time period. After that, $s^+$ values became relatively stable and the average number of actions per decision tree per agent fluctuates around 8 for predators, 6 for prey and 1.4 for neutral agents. In the $s^-$ setting, we observed the same trends but on a lower scale: the slope of average growth rate of complexity of decision trees is 0.007 for the first 100 generations, while the decision trees remain quite small, averaging around only 2 nodes for all $s^-$ sub-populations.

Analyzed data suggest that the main target of positive selective pressure is the diversity of actions an agent can perform. This raises the next question: is such diversification guided by the ability of agents to perceive environment or is it completely random? To answer that question we performed a detailed analysis of paths that agents executed over generations.

**Evolutionary Assimilation of Environment**

After the 10,000 $s^+$ generations, an average of 72.96% of all executed decision paths contain sense and sense-associated actions in predators, 64.13% in prey and 60% in neutral agents. Self-monitoring appears to be much less evolutionarily important (at least in this simplified setting): 22.96% of executed paths in predators contains self-monitoring, 21.74% in prey and 20% in neutral agents.

In summary, if we combine both sense and self-monitoring, 95.92% of all performed actions in predators are executed in a response to sensing some aspect of either the environment or itself. The results are somewhat smaller in prey (85.87%) and in neutral agents (80%). Nevertheless, they clearly show how essential and universal it is for agents to make sense of their environment.

In predators, the initial surge in the percent of executed paths with sense node happens already during the first 70 generations and then, after some instabilities, starts fluctuating between 40 – 60%, with slow upward trend (Fig 6).

However, these results are obtained in the environment with very high abundance of primary food (87.5% of all cells). To investigate the extent of agents actively using sense nodes in search for food, we ran additional scenario where primary food occupies only 30% of all cells. As expected, in prey agents the percentage of executed paths with sense significantly increased. Already during the first 300 generations it goes up to an average of 78% and continues to slowly grow over the next period reaching 82% after 10,000 generations. It is a 19% increase compared to the situation with abundant primary food. For predators, the percentage after 10,000 generations is almost the same (70%) as in the scenario with abundant primary food while for neutral agents it dropped 14% to 46%. Increase in perceptive assimilation of environment in prey agents strongly indicates the need to more actively forage for food. Why the perception of environment dropped so significantly in neutral agents is not entirely clear. It could be a consequence of a very small number of surviving neutral agents, such that random fluctuations became more prominent.

Self-monitoring in this “scarce” scenario remains at the similar levels as in the abundant food scenario: 23% of executed paths in predators, 16% in prey and 18% in neutral agents.

In total, after combining both sense and self-monitoring in “scarce” scenario, almost all executed action paths in predators and prey depend on perceptively assimilating either
Figure 6: Percentage of executed paths with sense node in predators during the first 300 generations. Inset shows the same percentage but over the first 1,000 generations with red line trend line.

external or internal cues (93% for predators and 98% for prey). The remaining 7% for predators and 2% for preys are executed randomly without any “reasoning” behind it.

Conclusions

Our model has several assumptions that significantly limit its scope. First, it is based on freely shuffling both elementary actions and the perceptual interpretations of the environment. However, the traits of real organisms are often coupled to each other either at the level of genotype (e.g. overlapping and linked genes) or phenotype (e.g. functional feedbacks in metabolic networks). On the other hand, as a rule of building decision trees we implemented a simple but rather restrictive structure of directed rooted trees. Such choice inherently rules out a number of possible ways how decision paths can be formed. Also, the model doesn’t have any independent external influences that can be harmful for evolvable agents, which are quite common in real ecosystems. Their introduction would probably increase selective pressure and widen the gap between agents that are aware of their environment compared to those which are ignorant of it. Nevertheless, despite these shortcomings, we believe that our findings can offer important insights in: (i) understanding the early evolution of both perception and functional organization of organisms and (ii) understanding how to design a new class of generalized evolvable systems not bounded by predefined goals.

Our starting hypothesis was to test whether purely random association of arbitrary environmental properties with latent elementary actions of agents can produce viable populations. The emergence of functionally different subpopulations and their long-term survival demonstrate that randomness coupled with natural selection is indeed the sufficient force to drive early evolution, at least in our simplified setting. Further, our results show that early evolutionary strategy of reconfigurable agents is mainly based on increases in the number of decision trees and then on increasing their complexity. Increase of the number of decision trees is much faster and last much longer compared to the other evolvable parameters. Also, most of the executed paths, which are extracted from decision trees, contains sense nodes. Overall, it seems that agents’ early evolutionary focus is to expand their ability to assimilate the environment and to functionally categorize the environment by developing a variety of adaptive responses to newly assimilated environmental properties as soon as possible. After the initial adaptive surge, rate of evolution slows down. These findings is generally in line with empirical findings - when faced with new environment, organisms evolve more rapidly (Ghalambor et al., 2015; Reznick and Ghalambor, 2001; Swings et al., 2017). The cause of the later slowdown of the evolution rate will be a subject of further research. Some possible causes are the constraints imposed by already developed mechanisms, or by reaching relatively optimal functioning in the new environment, or possibly by some other mechanism.

Also, in our model, the agents are able to survive without the ability to perceive and assimilate the environment. Indeed, $s^+$ evolution is much faster than $s^-$ but in both cases agents found the way to adapt. In the case of evolution with sense, the system settled in a cyclic interdependent shifts between a large number of prey and much smaller number of predators, as in real ecological systems. In the case of evolution without sense, populations are largely independent, but viable. Whether this is just a result of an over-simplified model universe (e.g. no independent harmful external influences) will be investigated in the forthcoming research. We plan to add independent harmful influences and generally increase complexity of the environment in the next installment of our model.

On the application side, we believe that our model could be a first step in developing a new class of generalized evolvable systems for applied machine learning problems. For example, the problem that is becoming increasingly important today is how to deal with the so-called unstructured data. The term applies to information that doesn’t have a pre-defined data model which organizes data into a well-defined format and structure. There is a number of domain specific approaches of how to deal with the problem (Istephan and Siadat, 2016; Subramaniyaswamy et al., 2015), but the generalized approach still does not exist. In the model presented here, agents learn how to recognize “messy” data and, in the parlance of data sciences, tag it with the appropriate data model. Such data model gradually standardizes how external data relate to each other and to the properties of external entities, from the perspective of the agent. So, we believe that this model could be modified to autonomously gather data and transform it from unstructured into a structured one.

Finally, this model allows to address a number of new
questions. For example, what would be the consequences of introducing mutually linked agent properties? Will the behavior of the agents be more complex if we introduce neural networks instead of trees? It would be very interesting to test what subpopulations will emerge in more complex environments. These are tasks for the forthcoming research.

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