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Title: Developmental Insights into Evolving Systems: Roles of Diversity, Non-Selection, Self-Organization, Symbiosis

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Developmental Insights into Evolving Systems: Roles of Diversity, Non-Selection, Self-Organization, Symbiosis

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Abstract

A developmental view of evolving systems (ecological, social, economical, organizational) is examined to clarify 1) the role of selection processes versus collective, non-selective processes, 2) the origins of diversity and its role in system performance and robustness 3) the origin of explicit subsystem interactions (cooperation/symbiosis) that enhance individual and system performance, 4) the preconditions necessary for further evolutionary development, and 5) the effect of environmental timescales with adaptation timescales. Three sequential stages of evolving systems (based on the work of Salthe) are proposed: a *Immature stage* dominated by highly decentralized, selective processes with chaotic local and global dynamics, a *Mature stage* dominated by non-selective, self-organizing processes with global robustness but locally chaotic dynamics, and a *Senescent stage* dominated by rigid interactions with global fragility. A simple model problem with many optimal and non-optimal solutions - an agent solution to a maze - illustrates the entire developmental history. Within the model, the agents evolve their capability from a random approach to an optimized performance by natural selection. As the agents develop improved capability, natural selection becomes rare, and an emergent collective solution is observed that is better than the performance of an average agent. As the collective, self-organizing structures are incorporated into individual capability within a stable environment, constraints arise in the agent's interactions, and the system loses diversity. The resulting Senescent system exhibits reduced randomness due to the rigid structures and ultimately becomes fragile. Depending on the degree environmental change, the Senescent system will either "die," or collapse under environmental stress to the Mature or Immature stage, or incorporate the constraints system-wide into a new hierarchical system. The current study adds to the literature on developmental systems by finding: Transitions between stages are dependent on the degree of sustained environmental stability and how exclusive cooperation (e.g., symbiosis) in a subsystem can originate, and how it results in a decline in diversity.

Introduction

One challenge for researches in evolving systems, whether for economic, ecological, political, social or organizational systems, is a common viewpoint for both understanding the dominant processes in their models and a basis by which to compare their models to others. The current work grew out of research on how self-organizing groups can solve problems better than experts and the consequent need to understand non-selective, self-organization processes[1] (Johnson et al. 1998) and how it relates to natural selection (Johnson 2000). Both selective and non-selective processes are observed in real systems and have validity. Both processes increase global fitness, but by distinctly different mechanisms. But, because each originates from very different viewpoints (competitive versus non-competitive agents), can they be reconciled into a single understanding? It was from this starting point that the current study began. A detailed examination of the dynamics and properties of non-selective self-organization was done (Johnson 1998), but offered no real insight into how this approach to global function related to selective processes. What was finally discovered was that these seemingly different approaches are representative of different stages of an evolving system (Johnson 2000). And the apparent conflict is resolved by a developmental perspective of evolution, based on the sustained work by Salthe

[1] An example of non-selective self-organization is foraging in social insects (Bonabeau et al. 1999), expressing what is called "swarm" intelligence. In the absence of selection (no ants die), a foraging group can be observed to perform greater than the capability of the individual (e.g., the path to the food is shorter for the average group than the best individual). These final paths represent the collective action of many individuals solving their own path problem, in a manner that is ultimately useful to the entire population but which is never expressed as a goal at the level of the individual. Another example is path formation in humans and the method for book referral used by Amazon.com (Johnson 1998).

(1989, 1993, 1999) for ecosystems. Within this developmental view, an extension of the model problem developed for non-selective self-organization is used to illustrate the full developmental history of evolving systems. This study begins to address many questions of interest in the fields of evolutionary systems: How do groups achieve higher global functionality? How can the robustness of the system be improved? What global properties are prerequisites for greater functionality? How does the system "boot-strap" itself to a higher functionality? The approach taken is review the developmental view of evolving systems, and then propose simple model problem to illustrate the stages of the theory and the mechanisms for transitions from one stage to another. While the simple model is not rich as real systems or highly developed simulation models, its simplicity enables clear discussion of the processes characterized by the general theory.

Developmental View of Systems

In this section a developmental view of evolving systems is presented, a summary of the work of Salthe (1989, 1993, 1999) and its extension to a other systems, economic, political, social, and organizational (Johnson 2000). The focus, here, is on the interplay of natural selection with non-selective processes, on the role of diversity, and on the transference of global emergent properties to subsystems. While three stages are presented below, it is understood that these are just points in a continuous development. Furthermore, to simplify the presentation, the systems are assumed to be homogeneous in the progress of maturation (subcomponents are not mixed across states). More likely, systems will have multiple stages of development simultaneously, particularly as a system increases in complexity and partially independent subsystems undergo cycles of maturation and failure and become out of phase.

Three stages for the development of any evolutionary system are: *Immature systems* - high selection pressure, rapid component and global variations, highly decentralized, low "complexity", low symbiosis (minimal interactions and dependencies), high entropy production; *Mature systems* - low selection pressure, high diversity, multiply interconnected and robust; *Senescent or aging systems* - similar to Mature systems, but interactions become restricted and rigid (lower variation in interactions - low entropy production), and the resulting system is fragile.

Table 1 presents a variety of properties for the different stages. The following definitions are used in the table. *Diversity* is the uniqueness of the attributes of the individuals. *Interconnectivity* is the degree of interaction between individuals/subsystems. *Chaotic dynamics* is the sensitivity of states (local or global) to small changes. *Decentralization* is the degree of autonomy of an individual's actions. *Individual flexibility* is the degree that the individual can survive changes in the environment or other sub-components; *system flexibility* (robustness) is the degree of survivability of the global system to environmental change or sub-component failure. *Entropy* is the measure per unit of the randomness expressed within the constraints of the system.

Immature Stage Immature systems are characterized by "hard" selection (Fisher 1930; Wallace 1970), with the corresponding aspects of relatively high competition and high mutation rates. The interdependence of individuals within Immature systems is initially low (highly decentralized), but increases as interdependencies and global structures form. Because of the role of selection for improving group fitness, diversity of the populations is essential for adaptation of the system to changes in environment. Because diversity is consumed by selection, diversity's role is as an investment for future adaptation and does not contribute to current system performance (the average state of the individual fitness) (Johnson 2000). In fact, the presence of diversity in an Immature system at any one time lowers system fitness because of high degree of individual failure.

Mature Stage The evolution of a Immature system to a Mature system is the creation of interdependency from the increasing diversity of individuals or subsystems (Kauffman 1993). As a consequence, overall system fitness shifts from a consequence of selection to improved fitness resulting from non-selective, self-organizing processes (Johnson 2000). Diversity in Mature systems is essential to the *current* fitness of the system and occurs, not as a result of new niche formation (a mechanism requiring selection), but just from the random processes of mutation without hard selection: *survival of the fittest becomes survival of the adequate* - also called soft selection (Salthe 1972; Wallace 1970). The development of global structures results in less chaotic dynamics on a global level, but the responsiveness of the system is retained by having chaotic dynamics at the local level (Johnson 1998). Similarly, the global system becomes more robust, due to redundancy and contingencies in the subsystems, a consequence of randomly generated diversity and the flexibility of the interdependencies between subsystems. Given sufficient environmental variability, the system will remain at a Mature state, because interdependencies are sufficiently dynamic to prevent rigid interdependencies from forming.

Property/Process	***Immature***	***Mature***	***Senescent***
Diversity	Increasing	High	Declining
Interconnectivity	Low and increasing	High and redundant	Declining and rigid
Chaotic dynamics:			
locally	High	High	Low
globally	High	Low	Low
Selection - Competition - Individual turnover	High	Low - preserves status quo	Low
Source of new diversity	Niche creation	Random generation	None
Group improvement	By individual selection	By collective processes	Same
Decentralization	High	Medium due to high interconnectivity	Low
Flexibility:			
individual	Low	High due to elastic interactions	Low
global	Varied	High due to redundancy	Low
Entropy production	High	Moderate	Low
Rate of environment change for stability	Varied	Slowly varying	None or little

Table 1: Stages of development in evolving systems.

Senescent Stage The transition from a Mature to Senescent system occurs as the consequence of a relatively stable environment. The self-organizing, flexible structures that are advantageous in the Mature state become exclusive, reinforced and rigid; entropy production is reduced. One form of these rigid structures is symbiotic (mutualistic or parasitic) relationships. Expressed another way, the emergent properties, and consequent advantages, in the Mature system are replaced by explicit (non-emergent) properties at the level of the individual. This is advantageous in a stable environment, because it eliminates the chaotic and unpredictable nature of a flexible, dynamics of the Mature stage. This transference is argued to be the origin of explicit cooperative behavior between individuals in many systems.

Death or Hierarchical Resolution The final outcome of the evolutionary cycle is dependent on many factors. One possibility is system-wide failure, resulting in the loss (death) of all constituents. While rigid structures in Senescent systems offer advantages to the subsystems, they are detrimental to the robustness of the global system. Senescent systems can fail if environmental stress is sufficient to break critical interdependencies. Then, due to the rigidity of the system, a global collapse of the system can result. From a global perspective, the collapse can return a Senescent system to a Mature or Immature stage. Alternatively, the advantageous rigid structures can be subsumed system-wide, and the evolutionary process can begin again on top of the structure. The adoption of DNA encoding or formation of a cell nucleus in life is an example of useful structures being incorporated system-wide, allowing variation then to occur on top of these global structures. The possibility that rigid structures can be subsumed system-wide is a path to developing hierarchical systems.

Examples of Each Stage

A prime example of a Immature systems is the field of Evolutionary programming and Genetic algorithms, summarized by Fogel (1999) and characterized by the use of algorithms using population-based variation and selection. Methods based on non-selective processes, such as the simulations presented in the Mature stage below, are absent.

An example of a Mature stage is a mature ecosystem, composed of diverse species, where each individual living to fulfil their own needs, resulting in a stable system that benefits all. While competition and selection occurs in Mature ecosystems, the global fitness (e.g., robustness) is due to the non-competitive interactions of a diverse community (Johnson 2000). The creation of new diversity is continual, not because of selection, but from lack of selection. The ecosystem is locally chaotic (species and individual interactions are unpredictable), but the global system is robust and insensitive to details of the chaotic nature. For social systems (organizational or political), most of the above observations for ecosystems can be also made. In particular, the unappreciated aspects of social networks in organizations provide problem solving capability and contingencies that directly result from diverse individuals or groups (Linstone 1999).

Examples of fully Senescent systems are rare due to their fragility. Very old ecosystems, such as the Australian rainforest that drains into the Great Barrier Reef, are good examples. Interactions are either highly specialized, such as a single species pollinating another single species, or highly restricted, such as the limited predators of the extremely poisonous tree frogs. The American automotive industry a decade ago reflected a system that was highly evolved but had limited flexibility, with few and fixed interdependencies.

A Model Problem of Evolution

A model problem is presented to illustrate the developmental perspective presented in the last section. The model problem as a Mature system has been studied in detail (Johnson 1998) and is extended here to the other stages. The model problem is the solution of a sequential problem (e.g., as in Fig. 1), which has many optimal and non-optimal solutions, solved by agents. While this maze problem in Fig. 1 is quite simple from a global perspective, it serves as a representation of more complex processes: the solution of a problem that has many decisions points and many possible solutions and that has difficulty greater than that solvable optimally by one individual. A more realistic landscape would not change the underlying processes that are observed in this simple model. It is argued (Johnson 1998) that all evolutionary systems are sequential in nature (every action of an individual has a prior, different action leading to the present state), and that the current model is an abstracted representation of real systems.

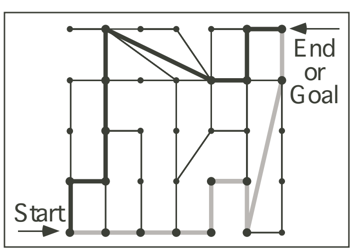

Figure 1: The example maze. Two of the 14 minimum length paths are highlighted.

The solution process for a single agent is divided into a *Learning phase* where simple rules of movement are used to explore and learn about the problem domain. Because the agents have no global sense of the problem, they initially explore the problem until the goal is found. The learning process can be thought of as an agent exploring the maze randomly and leaving "breadcrumbs" behind to aid in their search for the goal, thereby avoiding fruitless paths. Then in an *Application phase*, this "learned" information (bread crumbs or path preferences) is then used by the agent to solve the problem again, typically with a shorter path[2] as a consequence of eliminating unnecessary loops. Essentially, the agent in the Application phase follows the path with the most breadcrumbs.

The following assumptions are made and are discussed in detail elsewhere (Johnson 1998; Johnson 2000). These assumptions were analyzed and found to not be critical to the conclusions of this study. 1) The information available to an individual at a decision point (node) is independent of the path that they took to get there, i.e., the solution is path independent. Said alternatively, only local information is used in the decision - there is no global perspective by the individual. 2) Individuals "solve" the same problem, both in goals and in a common world view.[3] 3) Finally, individuals have identical assessment of the value of information.

Simulations of the Model Problem

A variety of strategies for an individual agent was used to solve the model problem (see Table 2). For example, the *random walk method* starts the agent at the beginning node, and then the next node is randomly selected. The process is repeated, each time selecting from all possible nodes connected to the present node, until the goal is reached. The *no-backstep random walk method* is the random selection of a new node excluding the node that was just vacated. And the *non-repeating random walk method* is the selection, if possible, of only untried links. The *Learning Rules* are a set of rules that mimic the idea of laying bread crumbs (or pheromones) down to aid the search - and giving more bread crumbs to the last link taken, so if the node is returned to and all nodes have been tried, then the last link used will be preferred.

These different Learning methods are differentiated by the degree the learned information used - from the extreme of being ignored in random walk to being optimized in the Learning Rules.[4] In the Application phase, the agents use the bread crumbs of the Learning phase to solve the maze again (see Table 2). The Application Rules are the same for all methods, and basically pick the path with the greatest "breadcrumbs."

[2]Note that "path length" is the number of segments in the path, not the actual path length.

[3]The common world view is taken to mean that the possible options that an agent has are identical. This does not mean that the preferred options are the same, only that the possible options are the same.

[4]Note that although multiple agents exist, *the agents solve the problem independent of the other agents*; this restriction is removed in Senescent version of the simulations.

Why is the performance in the Application phase better than in the Learning phase? Fig. 2 illustrates how an extraneous loop is eliminated by the Application phase for an individual. This mechanism is comparable to those argued for collective improvement in ant simulations (Bonabeau et al. 1999).

Learning method	Average	Standard deviation
Random walk (RW)	48.8 *(123)*	55 *(103)*
No-backstep RW	38.6 *(64)*	40 *(66)*
Non-repeating RW	33.7 *(51)*	36 *(51)*
Learning Rules	12.8 *(34)*	3.1 *(24)*

Table 2: Path Lengths for the Application phase for a population of 100 agents. The quantities in brackets are for the Learning phase.

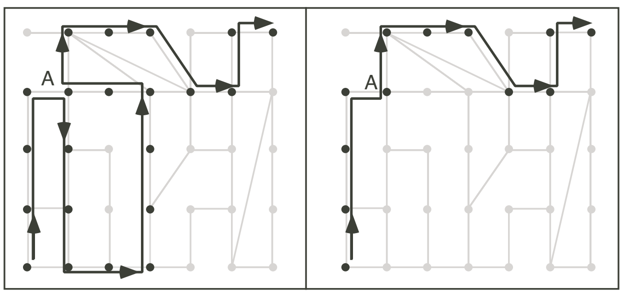

Figure 2: Plots of the paths in the two phases for a representative individual. The Application phase, at right, removes the extra loop at point A from the Learning phase, at left.

A Immature Stage of the Model Problem

The methods in Table 2 represent different strategies in solving the problem by an individual agent. While not implemented within the current simulations, a selective process can be developed where the agents with different strategies compete with each other, while repeatedly solving the maze, redoing the Learning and Application phases fresh each time. If the agents above a certain path length (number of links in a path) are eliminated and replaced with a new agent that uses a strategy sampled from the surviving agents (a genetic approach), then the population would become dominated by the most successful strategy - a typical result of natural selection. In the absence of mutations and with sufficient selection pressure, all diversity of capability would be lost.

Because the initial search is random, a collection of individuals using the same method shows a *diversity of experience* (knowledge of different regions of the maze), *diversity of preferences* (different preferred paths at any one location in the maze), and *diversity of performance* (different numbers of steps). The differences in "experiential" and "preferential" diversity, as opposed to capability diversity, are a direct consequence of the redundancy in the solution space of the problem: because there are many paths of equal length, there is no selection pressure for one path over another. If a selection pressure is added to encourage the agents to occupy vacant portions of the maze (say food sources) and if some "genetic" memory of the experience of the maze is passed onto new offspring ("turn left at node 5"), then the different regions of the maze would become equally populated. This is argued to be comparable to the "filling" of niches as a form for diversification in the process of natural selection. If a load-carrying capacity were defined to be the global fitness of a group of agents, then this experiential diversification would result in a maximum for global fitness.

The above description of a potential simulation scenario illustrates that the model problem can capture the attributes in Table 1 associated with Immature systems. Because of the predominance of natural selection in evolutionary approaches, comparable examples of Immature systems are abundant in the literature (Fogel 1999).

Mature Stage of the Model Problem

In this section the collective effects of having multiple agents solve a common problem is examined. The central question is how contributions from diverse agents can be organized in a manner that is useful to both the individuals and to the global system. The approach taken below is to present a collective solution to the model problem, but one which does not require individual interaction (competition or cooperation) or selection in any form. Therefore, the model problem is specifically constructed to isolate the emergent collective effects.

Forming a collective solution Suppose a group of individuals is heading to a cafe and all have prior experience with finding the cafe. At each corner, they combine their own experiences without discussion, and then chose a preferred path based on this collective information, using the same rules they each used as individuals. Said another way, suppose a group could see the bread crumbs of all of the members, and they pick the path with the greatest amount of bread crumbs. The realization of this metaphor in the current model problem is to use a linear combination of the each individual's experiences at each node in the maze for all the individuals in a group (Johnson 1998). Then the same Application rules as used for the individual are used on this group information to find a group solution. In some sense, the collective is a "super-informed" individual in that it has access to more information, but has the same capability as an individual. Figure 3 shows the simulation results for groups of increasing size for the different learning methods listed in Table 2. In Fig. 4, the simulations using the Learning Rules are shown (the Novice and Established concepts are discussed shortly). Because of the variation in performance for small groups, the simulations results in Figures 3 and 4 are ensemble averages of many simulations. To easily identify the improvement of the collective over the average performance of the individuals in the group (*the collective advantage*), the collective path lengths are normalized by the average of the performance of the individuals making up the ensemble (around 12.8 on average).

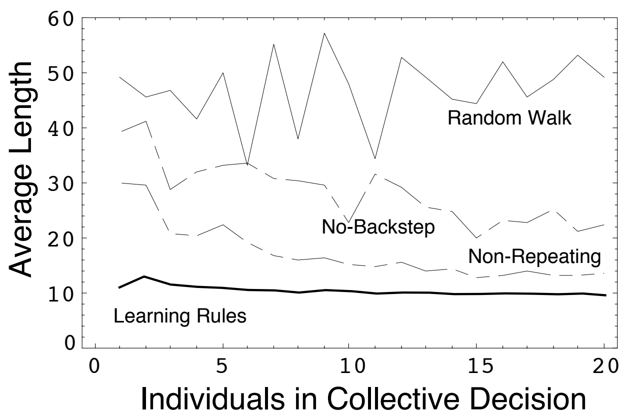

Figure 3: The path length for different numbers of groups of individuals using the various rules in Table 2. Each point on a curve is an average of 50 simulations. The two curves for the novice are for a selection of different individuals in the group.

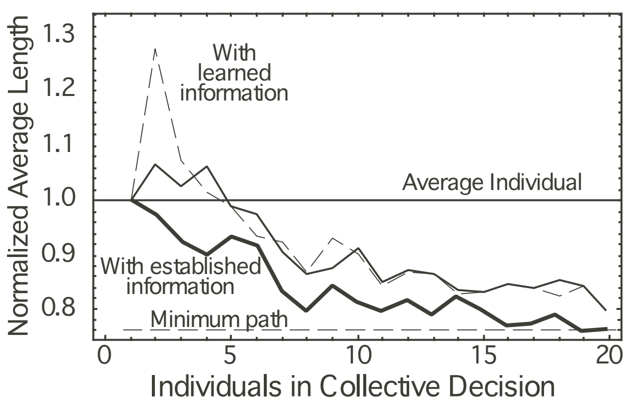

Figure 4: The normalized path length for different numbers of groups of individuals using the Learning Rules. The two curves for the "learned information" groups are for two different random selections of individuals.

In the repeated solution to an unchanging problem, we tend to remember only the information that is needed and forget extraneous information associated with unused paths. Here, the equivalent effect is for the agent to remember only "established" or reinforced information along paths, thereby "forgetting" unused paths. The process of forgetting unused information does not change the performance of an individual agent, because both the learned and established information produces the same path in the Application phase. An established individual experience is created from the learned experience by retaining information used in an individual solution, and forgetting unused information (e.g., the information used on the right in Fig. 2). In Fig. 4, the collective performance of the learned and established individual information is shown. The significance of the difference in performance is discussed in the section below on diversity.

The Collective Advantage as Emergence The model problem is developed with three requirements: 1) rules of the agents do not use global information, 2) the agents do not include logic for finding a shorter path and 3) the agents learn and apply information independently (do not interact or cooperate). These three requirements assure that any observed global property or functionality cannot be predicted from the properties of the individual. In Figs. 3 and 4 we observe that, with the exception of the random walk simulation, large collectives perform better than the average individual making up the collective and for collectives of sufficient size using the Learning Rules, the collective solution converges to one of minimum paths (the other methods converge to a non-optimal solution, as noted below). Therefore, the occurrence of a shorter path length for large collectives over the average individual is an emergent property of the system.

One mechanism of the collective improvement is the collective equivalent of the elimination of extraneous loops, similar to process of improvement of the individual in Fig. 2. Because the collective bread crumbs are a superposition of the information of many individuals, collective bread crumbs can contain extraneous loops as observed in Fig. 2, but which are only partially closed in the individual contributions. Fig. 5 illustrates how this can occur. By combining the information of multiple individuals, collective bread crumbs contain complete information and the extraneous loops can be removed from the group path. This emergent global property was found to be a robust property of the model problem and insensitive to many alterations or removal of assumptions in the model (Johnson 1998). The only exception was for groups composed of individuals learning by the random walk method (discussed next).

What is the significance of an emergent global property in this model? Before explicit forms of symbiosis and interdependencies between individuals can evolve, there first needs to be some emergent expression of the advantages of dependencies (Hemelrijk 1997). This is the classic "boot-strapping" dilemma of all evolving systems (Kauffman 1993).

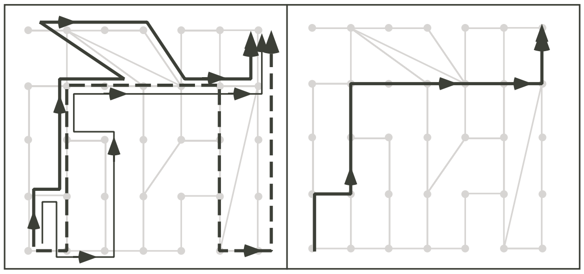

Figure 5: Paths of three individuals in the Learning phase, at left, combine to form the Collective Path, at right. Extraneous loops in the collective solution are eliminated from incomplete loops in the individual contributions.

The above discussion leads to the question of how the emergent capability in the model problem could be used by the individual or collective in a way which is not a consequence of explicit cooperation. The following variation is proposed. Suppose many individuals solve the maze simultaneously. At any given time, if there is more than one individual at a node, then a collective decision is made and the group continues to the next node together. Because the likelihood of the formation of a group is random and no selection of information from a subset of the group is made, this is an example of a combination of information that is both random and non-selective. The consequence is that the randomly formed group would follow the previously identified collective solution from that point on, assuming no other individuals are added to the group. If other individuals or groups are added during their progress to the goal, the additional members would only improve the collective solution.

Coupling of individual and group performance The results in Fig. 3 are essentially a study in which the problem difficulty (maze) is held constant and the individual's capability is varied. A comparable study was done in which the mazes were made more complex while the individual's capability was held constant (Johnson 1998). The following conclusions were drawn. 1) A simple maze to a good individual solver is trivial, and no collective advantage occurs. 2) Mazes of greater difficulty than can be trivially solved by an individual are solved optimally by large groups. 3) An extremely difficult maze to an individual with fixed capability leads to a random individual solution and no collective advantage is observed. These conclusions indicate that harder and harder problems cannot be solved by larger and larger groups of individuals with constant ability. Or, equivalently, the individual must have some capability (i.e., not random) which can be amplified in groups. These statements indicate that the collective advantage is coupled to the individual problem solving ability and the global problem difficulty. Hence, an essential aspect of the development of an evolving system can be identified: *the process of natural selection is needed to increase the performance of the individual to the point which the emergent global structures can amplify the weak individual signals.* This, then, explains why the groups formed from individuals that learn by the random walk method fail to show a collective advantage: there is no coherent signal that can be amplified by the collective solution.

	Collective Application Phase	
Learning Method	*Novice*	*Established*
Random Walk (RW)	32 (0.31)	21 (0.46)
No-Backstep RW	13 (0.32)	9 (0.42)
Non-Repeating RW	10 (0.30)	10 (0.44)
Learning Rules	9 (0.38)	9 (0.60)

Table 3: Path Lengths for the Application phase for different Learning phases for a population of 100. In the parentheses are the diversity measures.

Diversity and collective advantage What property of the group can be used to predict the occurrence of the collective advantage? The best correlation found was a measure of diversity which gives more weight to the contributions of the individuals that have the least commonality with the group - see (Johnson 1998) for a formal definition. In other words, individuals with potential experiences that are not shared by others are the most important. As shared potential experiences increase at a node, the weighting is less, until it is finally zero if all members of the group share the same potential experiences. The words "potential experience" are used, because no consideration is given to the magnitude of the preferences at a node.

In Table 3, a summary is given for collectives of 100 members for the various individual learning methods for a single simulation. The values of the experiential diversity are given - where the diversity is normalized such that it is between zero and one. Groups using established information are found to have a higher diversity measure and perform better than groups using novice information. Because the correlation for the results using the random walk learning method does not follow the same trend as the other simulations, this suggests that the effect captured by the experiential diversity measure is not the only reason for higher performance of the collective, and some accounting of quality of information, such as the relative performance of the individual, is also required.

Chaos and robustness in the simulations The model problem for the Mature stage expresses both chaos (locally) and robustness (globally). A detailed study of the local chaotic nature of the simulations (Johnson 1998) indicates, for example, that the specific path (sequence of nodes) of the collective solution is sensitive to the addition of one individual, even for arbitrarily large groups. This is a consequence of the problem domain containing multiple paths of equal fitness. But, the ability of the collective to find a minimum path is not chaotic, but is stable to small changes.

The robustness of the global solution can be demonstrated by also evaluating the sensitivity of the model problem to noise. Noise in this context is the random replacement of valid information in the individual's contribution to the collective, thereby creating *false* information. Fig. 6 shows the effect of the addition of noise in simulations with different frequencies: 0.0, 0.3, 0.7 and 0.9, where 0.0 represents the simulation using the Learning Rules in Fig. 2. These results are insensitive to the magnitude of the noise, as long as it is less than the maximum weighting of a path. The collective solution is observed to be remarkably insensitive to the addition of noise at low frequencies. Even at higher frequencies, the noise only delays the collective advantage to larger groups.[5] This is a clear demonstration how diversity makes the collective decision robust. The above results support the conclusion that the diversity measure is also a measure for the robustness of the collective solution.

Senescent Stage of the Model Problem

The essential difference between the Mature and Senescent systems is the formation of rigid interactions in the place of flexible ones. In the model problem the Mature-Senescent transition is captured by the introduction of feedback of the collective experience to either individuals or groups during the Learning or Application phases. This approach is comparable to the feedback of the combined pheromone trails to the individuals paths in ant-motivated simulations (Bonabeau et al. 1999). While this added feature to the model problem has not been examined in detail, sufficient evidence suggests that the feedback effect is significant and has the expected consequences.

[5]Note that an individual performance is much more sensitive to noise than the collective. This occurs because noise leads an individual to parts of the maze for which they have no experience from the Learning phase. In unexplored regions, the Application Rules degenerate to a random walk approach. For collectives, particularly large collectives, experience is available throughout the entire maze and, therefore, the collective cannot be misdirected by false information to unknown parts of the maze.

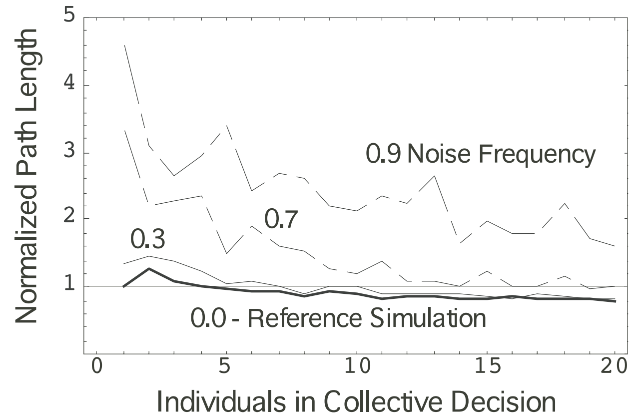

Figure 6: The effect of the random replacement of the individual's contribution to the collective for different frequencies of replacement.

Suppose in the Application phase of the collective, described in the prior section, as the groups increase in size they make use of the collective experience of the previous group. This was implemented in the simulations presented in Fig. 4 by letting the bread crumbs for the Application phase of the current group size be a linear combination of the previous group's bread crumbs and the current group's bread crumbs. This combined collective experience was then passed onto the next size group. When only 10 percent of the prior group's information is used, the convergence to a minimum path occurred by a group size of 8, instead of 20. Even more importantly, the local chaotic nature of the collective solution was lost: the same minimum path is selected as a consequence of the positive reinforcement of a single path in repeated collective solutions. Although not examined, the robustness to noise of this collective solution is expected to decrease with the loss of group diversity. These simulation results suggested the following analysis of the model problem.

Suppose in the following discussion that a collective experience has been generated, as describe in the section for the Mature stage. If this collective experience is used by a new individual during its Learning phase, then the individual will identically follow the choices made by the collective in the collective Application phase. A unique individual experience will not be created by the individual, because there is no random exploration that leads to diversity. This is because the individual begins the Learning phase with no experience (zero bread crumbs), and the presence of the collective experience will dominate the learning of the individual. The resulting individual experience from this collectively-enhanced learning process will cause the individual in its Application phase to duplicate (to within paths of equal preference) the path of the collective - a minimum path for large collectives. This process of individual learning based on the experience of the collective will filter out the information of alternative paths that were originally part of the collective experience, which was the basis for the system robustness. Hence, the individual achieves optimal performance, but at the cost of loss of individual robustness. If a new group is created from these "collectively-enhanced" individuals, they will express zero diversity and exhibit none of the robustness of the prior diverse collective. Furthermore, this "collectively-enhanced" group will perform optimally, but never better than the collective of identical individuals: the collective advantage will not occur, even if the "collectively-enhanced" individuals did not find a minimum path.

The above understanding is all within the context of a "stable" environment for the model problem: the beginning node and end node (goal) are unchanged in the above process. Suppose that the above process is repeated, but the end node is changed between the formation of the collective experience and the Learning phase of the "collectively-enhanced" individual. The consequence is that the collective experience would not correspond to the current goal, and the individual would resort to a random search, resulting in a return to a diverse population of individuals and a model performance similar to the Mature state describe earlier. If the goal change is not significantly different, then the system will come to a new equilibrium based on the old experience. If the goal is changed significantly, then the earlier structures (dominant paths) will be eliminated and replaced by new structures. If the simulations also included the "genetic selection" described in the Immature stage of the problem, the performance of the individual may be sufficiently poor to trigger a return to the Immature stage and selection of new capabilities.

The above process is argued to be the mechanism by which a diverse and robust population, as described in the Mature phase section become a Senescent system. In a stable environment, the emergent properties of the interactions (e.g., the collective path) can be incorporated by the individual to optimize their performance, but only at the expense of the loss of robustness of the collective. Depending on the rate of change in the environment, the system will either remain flexible in its interactions (slow rate of change for the Mature stage) or create rigid structures (no change for the transition from the Mature to Senescent stage) or lose all rigid structures (rapid change from the Senescent to Immature stage). In all of the above discussion the extent of the problem domain was unchanged. Supposed that the present maze is only one of many overlapping mazes, each with its own agents. Within this context, then, the formation of rigid structures on one level represents the incorporation of a subsystem structure, upon which further variation can occur on top of or around it. This models the formation of a hierarchical system (Mayer and Rasmussen 1998).

Summary

The main *theme* of this work is the presentation of a developmental theory of evolving systems (ecological, social, political, organizational). The main *purpose* is to understand of the roles of diversity and mechanisms of higher functionality by processes of non-selection. It is only within a developmental perspective that non-selective processes can be compared to the predominant explanation of natural selection as the source of functionality in evolving systems.

The developmental view of evolution identifies three sequential stages: a *Immature* stage dominated by highly decentralized, selective processes and chaotic dynamics (local and global), a *Mature* stage dominated by non-selective, self-organizing processes and global robustness, and a *Senescent* stage dominated by rigid interactions and global fragility. The allowable transitions of an evolving system through these developmental stages depend both on the rate of environmental change (external pressure) and the occurrence of prerequisite processes of the stage before. These prerequisites are 1) high diversity of individuals, 2) sufficient local interconnectivity between individuals or subsystems, 3) sufficient capability of the individual relative to the global challenges that can be amplified by self-organizing processes, and 4) mechanisms for the capturing of emergent properties at the global level in the individual properties.

A model problem was proposed and used to illustrate the processes and transitions of a developmental view. It is significant that one simple model yields insights into abstract concepts (self-organization, selection, diversity, robustness, origin of cooperation, etc.) and lends credence to the view that a sequential problem with multiple solutions solved by an diverse agents is an appropriate general model for evolving systems. Comparable model problems of evolution of the iterated prisoner's dilemma and cellular automata are not as general.

The following insights into developmental systems are captured by the simple model. 1) Diversity is best defined as the measure of the uniqueness of the members in a group. This measure correlates consistently with group or system robustness for all the stages and for the non-selective, self-organizing collective advantage. 2) Diversity is expressed in rich systems in many ways: capability, experience, preferences and performance. Selection in a system may reduce one type of diversity, but may not affect other types. 3) Diversity can arise at random in groups of agents *of identical capability* when a system has little or no selection pressure (survival of the adequate, instead of survival of the fittest). Diversity does not have to arise by selection or from agents of different capability. 4) Random creation of diversity can contribute directly to both global performance (collective self-organization) and robustness, above that of an individual and in the absence of any selection from the population. 5) The process of collective, non-selective self-organization can duplicate the system-wide advantages of explicit cooperation. 6) The performance of the collective self-organization is coupled to the individual performance and global problem difficulty. 7) These emergent processes are the precursors of cooperative advantages that are often attributed to individuals and are the key transitional mechanism from the Mature to Senescent stage. 8) Mature systems can express both local chaos (entropy) and global stability (robustness) simultaneously. Both are a direct consequence of the diversity of the system. 9) Exclusive and explicit interdependencies, characteristic of the Senescent stage, reduce entropy/diversity and consequently the robustness of a system. These interdependencies are a transfer of the collective self-organization properties observed in the Mature phase into the properties of the individuals. These explicit interdependencies form only in stable environments. 10) Hierarchical systems can form by the incorporation of these exclusive interactions into global structures, thereby, creating a new landscape for variation and return to an Immature or Mature stage of development.

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