Self-organization in Communicating Groups: the emergence of coordination, shared references and collective intelligence

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0. Introduction

In the last few decades a new scientific paradigm has been slowly emerging: *complexity* [Waldrop, 1992; Heylighen, 2008; Heylighen, Cilliers & Gershenson, 2007]. This paradigm departs from the reductionism, determinism and materialism of classical, Newtonian science by focusing on the non-linear interactions between the components of a complex system. Out of these interactions new properties or forms of organization emerge, a phenomenon termed *self-organization*. The present paper will sketch the basic ideas of the complexity paradigm, and then apply them to social systems, and in particular to groups of communicating individuals who together need to agree about how to tackle some problem or how to coordinate their actions.

This is a very common situation in any kind of social interaction: individuals typically come to the table with different backgrounds, habits, ideas, cultures, perspectives and even languages. To be able to communicate at all, they should first agree about a common set of terms and what those terms mean. This is the emergence of linguistic conventions. Then they should agree about basic assumptions, such as what the situation is, what can be done about it, and what should be done about it. Finally, they will need to agree about who will do what when. If successful, this sequence of agreements will lead to a coordinated form of action, where the different members of the group contribute in an efficient way to a collective solution of whatever their problem was. This phenomenon, where a group of initially independent agents develop a collective approach to the tackling of some shared problem that is more powerful than the approach any of them might have developed individually, may be called *collective intelligence* [Heylighen 1999; Lévy, 1997].

The emergence of collective intelligence is intrinsically a process of self-organization. If the process were directed by a single individual (say, the group leader), who imposes a consensus view on the others, then that perspective would not be more powerful than the perspective of the leading individual. In other words, the collective would not be in any way more intelligent than its leader. Self-organization happens in a distributed or decentralized manner: the different members of the group all contribute to the emerging organization, and no one is in control. This makes the process complex and intrinsically unpredictable, as tiny differences in the initial state (such as who speaks first, or which word is initially used to designate a particular item) may lead to very different outcomes. That is why such a process of group discussion and emergent interaction patterns needs to be understood with the conceptual tools of complexity science.

The paper will start with a short review of these concepts, contrasting them with the older, Newtonian paradigm. I will then elaborate these concepts to provide an integrated foundation for a theory of self-organization, to be understood as a non-linear process of spontaneous coordination between actions. Such coordination will be shown to consist of the following components: alignment, division of labor, workflow and aggregation. I will then review some paradigmatic simulations and experiments that illustrate the alignment of references and communicative conventions between communicating agents. Finally, the paper will summarize the preliminary results of a series of experiments that I devised in order to observe the emergence of collective intelligence within a communicating group, and interpret these observations in terms of alignment, division of labor and workflow.

1. Complex Systems

Classical science, as exemplified by Newtonian mechanics, is essentially reductionist: it reduces all complex phenomena to their simplest components, and then tries to describe these components in a complete, objective and deterministic manner [Prigogine & Stengers, 1984; Gershenson & Heylighen, 2005; Heylighen, Cilliers & Gershenson, 2007]. The philosophy of complexity is that this is in general impossible: complex systems, such as organisms, societies, languages, or the Internet, have properties—emergent properties—that cannot be reduced to the mere properties of their parts. Moreover, the behavior of these systems has aspects that are intrinsically unpredictable and uncontrollable, and that cannot be described in any complete manner. Finally, Newtonian mechanics assumes that all changes are reversible, and therefore that there is no fundamental difference between the past and the future. Complex systems, on the other hand, are characterized by an irreversible evolution, by an "arrow of time" that points unambiguously from the past to the future, and that allows no turning back [Prigogine & Stengers, 1984].

While these observations are mostly negative, emphasizing the traditional qualities that complex systems lack, complex systems also have a number of surprisingly positive features, such as adaptivity, autonomy and robustness, that traditional mechanistic systems lack. These qualities can all be seen as aspects of the process of self-organization that typifies complex systems: these systems spontaneously organize themselves so as to better cope with various internal and external problems and perturbations. This allows them to evolve and adapt to a constantly changing environment. Thus, the arrow of time tends to point towards an improved, better organized or more adapted version of the evolving system [Stewart, 2000]. This adaptive organization produced by self-organizing evolution can be seen as a form of knowledge or intelligence: the system has become better at solving the problems that confront it; it now "knows" what to do when confronted with a perturbation [Heylighen, 2007b].

More fundamentally, the complex systems approach has done away with the old philosophy of dualism, which sees the world as made out of two distinct substances: *matter*, as described by the natural sciences, and *mind*, as described by the social sciences and humanities. In the systems approach, matter and mind are merely two different aspects of the same basic phenomenon of *organization*, with matter representing the simple, static, passive, causally determined aspects, and mind the more complex, dynamic, active, goal-directed aspects. As systems evolve, starting from elementary particles via atoms, molecules and organisms to brains, societies, languages and cultures, they become more complex and adaptive, and therefore more "mind-like" and less "matter-like". However, that does not mean that mind should be understood merely as a complex arrangement of pieces of matter: the material components themselves can already be conceptualized as having rudimentary "mind-like" qualities, such as sensitivity, intention, and action [Heylighen, 2011]. For example, a molecule may sense the presence of another molecule and act upon that molecule via electromagnetic interaction between the charged atoms in the molecule. Its implicit "goal" or "intention" in that interaction is to find a configuration that minimizes its potential energy.

The components of a complex system are commonly called *agents*. These are individual systems that act upon their environment in response to the events they sense or experience. Typical examples of agents used in complex system models are people, firms, animals, cells, computer programs and molecules. Usually, agents are assumed to be goal-directed: their actions aim to maximize their individual "fitness", "utility" or "preference". In that sense, their actions can be seen as *intentional* [Heylighen, 2011]: they are performed so as to achieve a particular purpose or objective. When no explicit goal can be distinguished, their activity still follows a simple cause-and-effect or condition-action logic: an agent will react to a specific condition perceived in the environment (cause) by producing an appropriate action (effect). However, this causal perspective is essentially equivalent to the intentional perspective (which Dennett [1989] calls the *intentional stance*), because irreversible actions eventually lead to a so-called "attractor" of the agent's dynamics, and an attractor behaves indistinguishably from a goal or intention. This is the most fundamental sense in which the complex systems approach transcends the mind-matter duality: causal (material) and intentional (mental) models are essentially equivalent—even though the one may be more easily applicable in a certain context than the other.

The environmental conditions to which an agent reacts are normally affected by other agents' activities. Therefore, an action by one agent will in general trigger further actions by one or more other agents, possibly setting in motion an extended chain of activity that propagates from agent to agent across the system. Such interactions are initially local: they start out affecting only the agents in the immediate neighborhood of the initial actor. However, their consequences are often global, affecting the system of agents as a whole, like a ripple produced by a pebble that locally disturbs the surface of the water, but then widens to encompass the whole pond.

The spreading of a wave is not a complex phenomenon, though, because its propagation is perfectly regular and predictable, and its intensity diminishes as its reach widens. Processes in complex systems, on the other hand, are usually *non-linear*: their effects are not proportional to their causes. When the effects are larger than the causes, we may say that there is an amplification or positive feedback: initially small perturbations reinforce themselves so as to become ever more intense. An example is the spread of a disease, where a single infection may eventually turn into a global pandemic. Another example is the chain reaction that leads to a nuclear explosion. When the effects are smaller than the causes, there is a dampening or negative feedback: perturbations are gradually reduced, until the system returns to its equilibrium state.

Interactions with positive feedback are very *sensitive to their initial conditions*: a change in that condition may be so small that it is intrinsically undetectable, yet results in a drastically altered outcome. This is called the *butterfly effect* after the observation that, because of the non-linearity of the system of equations governing the weather, the flapping of the wings of a butterfly in Tokyo may cause a hurricane in New York. The non-observability of the initial perturbations means that the outcome is in principle unpredictable, even if the dynamics of the system were perfectly deterministic: no weather monitoring system can be so accurate that it senses all the movements of butterfly wings… This explains why weather forecasts cannot be fully reliable, especially for the longer term. Positive feedback will amplify small, random fluctuations into wild, unpredictable swings, making the overall behavior of the system *chaotic*. An illustration can be found in the erratic up-and-down movements of quotations on the stock exchange.

2. Self-organization

The concept of self-organization is becoming increasingly popular in various branches of science and technology. Although there is no generally accepted definition [Gershenson & Heylighen, 2003], a self-organizing system may be characterized by global, coordinated activity arising spontaneously from local interactions between the system's components or "agents". This activity is distributed over all components, without a central controller supervising or directing the behavior. For example, in a school of fish each individual fish bases its behavior on its perception of the position and speed of its immediate neighbors, rather than on the behavior of a "central fish" or that of the whole school. Self-organization establishes a relation between the behavior of the individual components and the structure and functionality of the system as a whole: simple interactions at the local level give rise to complex patterns at the global level. This phenomenon is called *emergence*.

The term "self-organization" was first proposed by the cybernetician Ashby [Ashby, 1947]. He noted that a dynamic system left on its own will spontaneously evolve towards what we now call an "attractor": a stable regime of activity towards which the system will tend to return even if disturbed. He further noted that in this regime the different components of the system are in a sense mutually adapted, so that they function in a coordinated, "organized" manner. In 1960, the first conference on self-organizing systems was organized [Yovitts & Cameron, 1960]. One of the contributors, von Foerster [1960], formulated another fundamental mechanism: the "order from noise" principle, which notes that the more random variation (noise) the system is subjected to, the faster it will self-organize (create order).

A similar principle, "order through fluctuations", was formulated a couple of years later by the Nobel-prize winning chemist Prigogine [Nicolis & Prigogine, 1977], who applied self-organization to explain the "dissipative structures" that appear in thermodynamic systems far from equilibrium. In the same period, the physicist Haken [1977] founded the domain of synergetics, a mathematical approach towards understanding the spontaneous cooperation that emerges in systems with many components, as exemplified by lasers and phase transitions. Another early application of self-organizing mechanisms were neural networks: computer simulations of how the neurons in the brain perform complex tasks (such as learning, classification, and pattern recognition) in a very robust manner without centralized control.

In the 1980s and 90s, the study of self-organization was deepened by the mathematical models from non-linear dynamics and chaos theory [Strogatz, 2000], and by multi-agent computer simulations, which allowed the investigation of systems too complex to be modeled analytically. This led to the emergence of the field of complex (adaptive) systems (see, e.g., [Holland, 1992, 1996]), which studies systems consisting of many interacting components, such as societies, markets, ecosystems, and the Internet. Most recently, the notion of self-organization has become popular in computer science and engineering, as a means to design robust systems that can function without centralized control (see e.g. [Elmenreich et al., 2009]).

At present, the concept of self-organization has diffused into virtually all scientific disciplines, as an explanation for previously mysterious phenomena in which complex structures arise from the interactions between simpler components. For example, it has been used in cosmology to explain the emergence of order in the universe [Jantsch, 1980]; in ecology to understand the evolution of complex ecosystems [Odum, 1989]; in biology to study the coordination between bacteria, cells or individuals in animal collectives, such as ant hills, schools of fish or swarms of birds [Camazine et al., 2003]; in medicine, to explain complex disorders such as epilepsy, heart disease and cancer [Coffey, 1998]; in linguistics, to model the origins of lexicons, grammars and phonetic systems [Steels, 2005; de Boer, 2000a,b]; in psychology to explain the emergence of higher level cognitive structures [Stadler & Kruse, 1990; Thelen, 1989]; in sociology and management to compare controlled, top-down organizations with spontaneous, bottom-up communities [Coleman, 1999]; in economics to better understand the "invisible hand" that governs the market [Witt, 2006]; in geography, to study cities and regions as self-organizing systems [Allen, 1997]; in robotics as a strategy to get simple agents to tackle complex tasks collaboratively [Holland & Melhuish, 1999]; in philosophy as a foundation for a new evolutionary worldview spanning all levels from matter via life to mind and society [Jantsch, 1980; Prigogine & Stengers, 1984; Heylighen, Cilliers & Gershenson, 2007].

It seems almost as if the concept of self-organization offers a key to unlock a treasure chest of new theories and applications throughout science, doing away with all the rigidities and limitations of the traditional "top-down", mechanistic approach. In spite of these promises, however, the science of self-organization [Heylighen, 2002] is still in its infancy. Researchers in different disciplines have studied a variety of examples of self-organization, but they typically take different perspectives and analyze different aspects. This makes self-organization a dynamic, but heterogeneous and rather confusing field.

In the following, I will therefore try to formulate a general conceptual foundation for the study of self-organization, and apply this to the emergence of collective intelligence in groups. This is an extension and clarification of my earlier work on the theory of self-organization [Heylighen, 2002, 2009; Gershenson & Heylighen, 2003]. It will require first of all an analysis of the concept of organization.

3. Self-organization as a problem of coordination

Organization can be defined as *structure with function*: the components (agents) of the system are arranged in an orderly way (structure) so as to achieve a certain goal (function). This is the meaning used in sociology and management: a typical organization, such as a company or government institute, consists of individuals who are arranged according to specified lines of communication and control. This structure is intended to facilitate the work of the organization towards its goals, such as providing a product or service. When we reflect a little more deeply, though, the notion of structure tell us very little about how this arrangement is supposed to contribute to the achievement of a function. Why cannot the same goal be reached by an anarchic group of autonomous individuals each contributing his or her best effort?

The relation between structure and function becomes clearer when we introduce the notion of *coordination* [Crowston et al., 2006]: what counts is not so much how individual agents are arranged (e.g. in some kind of hierarchy or network), but how their actions work together in a harmonic way towards their collective goals. At the very least, these actions should not hinder, obstruct, or oppose each other. This is what I have called the avoidance of *friction* [Heylighen, 2007b, 2008, 2011]. At best, they will smoothly complement each other, the one continuing the task where the other one stopped, or the one adding the necessary ingredient that the other one lacked. As such they can solve problems together that they cannot solve individually. This bonus added by collaboration may be called *synergy* [Corning, 1998; Heylighen, 2007, 2008]. *Coordination* can then be defined as: *the structuring of actions in time and (social) space so as to minimize friction and maximize synergy between these actions*.

Coordination can be subdivided in four elementary processes or mechanisms: *alignment*, *division of labor, workflow*, and *aggregation*, which I will now discuss in turn.

3.1. *Self-organization of Alignment*

Alignment is the simplest form of coordination. It means that the different actions (and therefore also their agents) “point in the same direction”, or, more precisely, *aim at the same target*. Every (intended) action has an implicit goal or target, which is the situation that would be reached if the action would be performed without any perturbation or obstruction throwing it off-course [Heylighen, 2011]. Imagine two individuals simultaneously pushing against a heavy object to get it out of the way. If the one pushes to the left (direction or target of the push), and the other to the right, their actions will oppose and thus obstruct each other. Assuming that the forces with which they push are equal, the result is that the object will not move at all, even though both agents may spend all of their energy pushing it. This is an extreme example of friction caused by a complete lack of alignment. Friction does not in general imply *conflict* between the agents, though. Perhaps the two individuals really want to reach the same overall goal, such as getting the obstacle off the road. However, because their actions are not coordinated, they effectively oppose each other. To minimize friction, they should somehow come to push in the same direction, i.e. *align* their actions.

Alignment is in general easy to achieve by self-organization. Assume that the two agents cannot see each other, so that they have no idea a priori of what the other is doing. Still, when pushing in opposite directions they will feel that their movement is blocked. Therefore, their natural reaction will be to try and push in a different direction. If the new push is not opposed by the other’s push, the obstacle will move, and the agents will continue to push in that direction. With a little bit of trial-and-error they may further discover that by pushing in one precise direction, their push is not only not hindered, but actually fully reinforced by the other one who is pushing in the same direction. Once they discover this shared direction, their actions are fully aligned, and their effort is maximally productive. Therefore, each of them will continue to push in that direction, even without knowing that the other one is doing the same.

This example illustrates the mechanism of self-organization at the most elementary level. An action that is not succesful will normally be varied (*variation*). On the other hand, an action that is successful will be maintained or reinforced (*selective retention or multiplication*). Successful actions are characterized by minimal friction and maximal synergy. Therefore, the evolutionary mechanism of the blind-variation-and-natural-selection of actions will sooner or latter produce an interaction that is more synergetic and less frictional. This mechanism does not require any planning, knowledge, or intelligence on the part of the agents. The only assumption is that the agents obey a logic of trial-and-error or variation-and-selection, producing a variety of actions until they find one that is maximally productive and stick to that one, irrespective of what causes that increase in productivity. Therefore, self-organization is a process that occurs at all levels, from atoms to societies.

Note that this mechanism synthesizes the principles of self-organization originally formulated by the founding fathers of the domain. Ashby [1947, 1962] conceived self-organization as the automatic "selection" of stable states (attractors) by a dynamic system. Von Foerster [1960] and Prigogine [Nicolis & Prigogine, 1977; Prigogine & Stengers, 1984] added that such attractors will be reached more quickly by injecting "random" or blind variation into the system, a principle they called "order from noise", "order through fluctuations", or "order out of chaos".

We next need to explain how alignment can extend from a pair of agents to a group. Suppose three individuals are pushing against the object. If two by chance align, the object will tend to start moving in the direction of their alignment. The third agent will now quickly discover that the best way for it to move the object is to push in the same direction. The same logic applies to a fourth, fifth, etc. agent. The more are already aligned, the larger the force in the direction of their alignment, the more difficult it will be for others to oppose that movement, but the easier it will be for them to join in with that movement. Therefore, trial-and-error on the part of those others will settle more quickly on the direction of the initial alignment. This is a process of *positive feedback*: the more alignment there already is, the faster others will join it. As a result, all agents will quickly align, making the collective homogeneous in its direction of action (see Fig. 1)

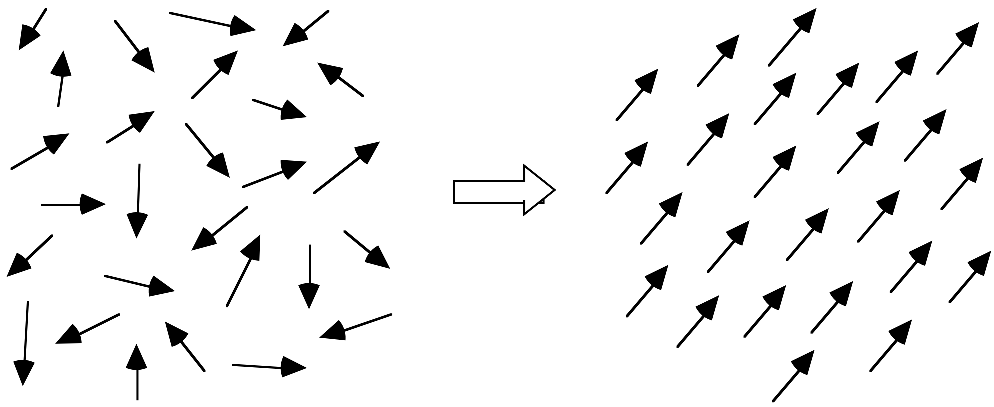

Figure 1: global alignment of directions of action, from random (left) to homogeneous (right)

If the agents are spread across an extended region of space, it may take a while for the alignment to propagate across that space, as more remote agents will initially not sense that in another region an alignment has started to form. Instead, the agents in one region may start to align on one direction, while those in another region align on a different direction. In this case, the space may subdivide into differently aligned regions (Fig. 2). This creates local homogeneity, but global heterogeneity. The borders between the regions will tend to be in the spaces where the initial interaction between agents are weakest, because agents are most likely to align with the neighbors they have the strongest interactions with. Along these borders, there is no alignment, and therefore there is still friction.

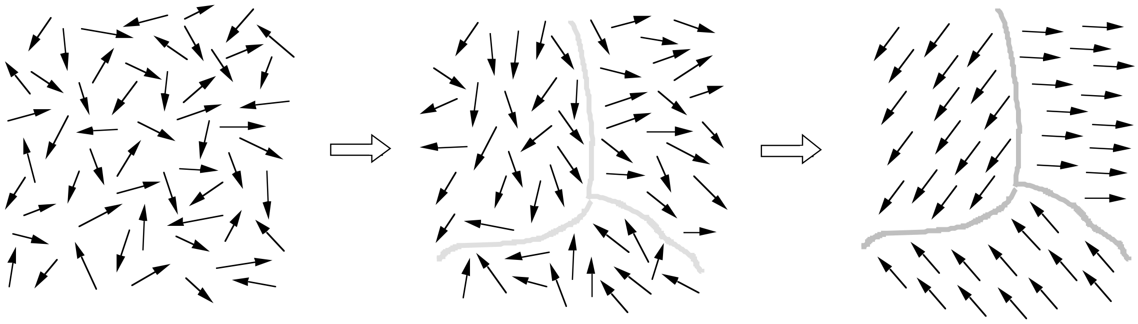

Figure 2: local alignment of directions of action, from random (left) to locally homogeneous, but globally heterogeneous (right)

This local or global homogeneization is a very common process in a variety of domains. Figures 1 and 2 were originally drawn to depict a process of self-organized magnetization [Heylighen, 2006], in which a number of magnetized molecules, each with a magnetic field that initially pointed in a random direction, eventually become aligned—globally or regionally. The "goal" of these molecules is to minimize potential energy. This is achieved when their fields point in the same direction, because the North pole (arrow end) of a magnet is attracted by the South pole (non-arrow end) of a neighboring magnet, while two North poles or two South poles repel each other. Therefore, arrows pointing in opposite directions repel each other (friction), and thus will induce a change in direction, while aligned arrows will attract and therefore stabilize each other's direction.

Another classic example of such local alignment is cultural homogeneization, where people in a frequently interacting group will tend to converge in their dialects, beliefs, attitudes and habits, while diverging from neighboring groups with which there is less interaction [Axelrod, 1997; Van Overwalle & Heylighen, 2006]. This is the origin of relatively homogeneous cultural groups such as languages, religions, and ethnicities. As noted, the boundary between such culturally homogeneous groups is the place where most friction remains. [Lim et al., 2007] made a computer simulation of social self-organization that illustrates how locally homogeneous regions can emerge from an initially heterogeneous population. By focusing on the boundaries between these emerging regions, the simulation managed to successfully predict the spots where conflict would erupt in ethnically heterogeneous countries such as former Yugoslavia and India. We will examine such communicative convergence in more detail later.

3.2. Division of Labor

Alignment of agents and their actions is a first requirement for them to work in a coordinated, organized manner. However, if all agents merely act in the same way, their combined action will be at most quantitatively more powerful than their individual action. For example, ten agents can push a weight that is ten times as heavy than the weight pushed by a single agent. But you cannot build a house using only agents that lay bricks; you will also need the expertise to dig foundations, do carpentry, lay electricity, install plumbing, paint, etc. To reap the full benefits of cooperation, different actions need to complement each other. Only then can the activity as a whole achieve more than the sum of its parts.

This assumes that different agents perform different tasks, each specializing in what it does best. Since each agent is limited in its abilities, the one may compensate for what the other one lacks so that together they can solve a problem that requires a diverse array of skills. But the problem then becomes one of the *division of labor*: who does what? Assuming that there is a variety of different tasks to be done, and a variety of skills distributed among the different agents, so that each agent is skilled at different tasks to different degrees, the coordination problem becomes one of optimally matching each individual with each task. At first sight, this requires a supervisor having an extensive knowledge both of the necessary tasks and of the individuals' degree of skills, and the intelligence necessary to conceive of all the different possible permutations of agent-task assignments and to select the best one.

Yet, the problem allows for a simple, self-organizing solution. Assume that agents prefer to do the tasks they are most skilled at, because those are the ones that will cost them least effort. In that case, it suffices for the different tasks to be laid out in such a way that all available agents can examine them. As soon as an agent recognizes a task that it is particularly skilled at, it will pick up that task, leaving less fitting tasks for the others. Thus, the number of remaining tasks will gradually diminish. There is of course the risk that the remaining tasks fit none of the remaining agents, but we can make the assumption that all agents are flexible to some degree and can if necessary do a task they are not particularly skilled at, albeit less efficiently. In this way, the different tasks will get performed in an overall rather efficient way, although the arrangement may not be optimal. (Such less-than-optimal, but more-than-acceptable performance is what we normally find in the real world, as opposed to the idealized world of mathematical models, where things tend to work either perfectly, or not at all…).

One example of such self-organizing division of labor is Wikipedia, the Internet encyclopedia that is being written collaboratively by millions of people worldwide. No "editor-in-chief" has divided the labor among the contributors, by specifying which expert should write a page on which subject, as is done in traditional encyclopedias. Instead, the "experts" have self-selected by starting to write, adding to, or correcting any page for which they felt they had sufficient competence to make a contribution. Thus, a football supporter may add something about the scoring percentages of his favorite team, while a butterfly collector may contribute something about the color patterns of her favorite species.

Another example of such self-selected specialization is an ecosystem in which different species specialize in exploiting different niches. Individuals of each species will explore many different habitats and ways of life withing their complex environment. If they find one that suits them, they will stay and thrive. If the present one does not suit them, they will move on until they find a better one (or be eliminated from the scene). Thus, different species and individuals specialize in exploiting the different niches that are available.

With some minor variations, the same process happens in a market economy: different businesses spread out and specialize so as to maximally fill each of the available niches, i.e. delivering the specific products and services for which there is sufficient demand, and for which their competence in delivering it is at least as good as the one of their competitors. This form of self-organizing allocation of agents (firms) to tasks (supplying goods and services) is sometimes referred to as the "invisible hand" of the market [Witt, 2006]. While in practice the solution will never be optimal, it has proven to be far superior to the alternative of a centralized economic planning, as practiced e.g. in the Soviet Union. The reason is that the "calculation problem" of establishing exactly how many goods of which type need to be delivered by whom is much too complex to be solved by any planner. Only self-organization can produce robust solutions to problems of such complexity and variability.

3.3. Workflow

Division of labor coordinates activities that happen simultaneously—in parallel. *Workflow* [van der Aalst & van Hee, 2004] is its complement: it coordinates activities that take place the one after the other—sequentially. The name derives from the image of an unfinished piece of work "flowing" from one worker to the next, as if carrried by a conveyor belt in a factory assembly line. In general, a complex activity, such as building a house, happens in subsequent stages, and the later stages (such as painting the walls) cannot be performed before the earlier ones (such as building a roof and plastering the walls) have been finished. Planning and scheduling such a branching sequence of mutually dependent activities may seem to require an intelligent and knowledgeable supervisor, supported perhaps by specialized management tools, such as Gantt charts or PERT networks. Again, self-organizing solutions to the problem exist that function quite effectively.

The mechanism is similar to the one underlying the division of labor. An agent that has finished the task it initially selected will normally look around for other tasks that might fit its profile. If one of those tasks becomes available, e.g. because another agent just finished executing that part of an activity it felt competent at, but stopped when it no longer felt able to continue, the first agent will pick up the work where the other one left off. For example, a brick layer may leave a wall as soon as all the bricks are in place, and thus make room for a plasterer to cover and smoothen the rough brick surface. When the plaster covering has dried, a painter may then finish the work by coating the wall with paint.

While this type of spontaneous follow-up is rare in modern, centrally managed organizations, it is the rule in animal collaboration. For example, an antelope being chased by, but escaping from, one lion, may run straight into the path of another lion who is waiting in the bushes, ready to jump when the antelope comes near. In this way, the lions (or other cooperating predators) can coordinate their actions without need for central planning. Social insects, such as ants and termites, similarly perform complex activities both sequentially and in parallel, the one taking over from the other whenever the occasion presents itself to carry on with a task that is unfinished. The same type of spontaneous follow-up happens in conversations or group discussions where one person proposes an idea which then inspires another one to add a further refinement, which then may elicit a correction from a third person, etc.

As long as a large enough number of agents with sufficiently diverse or broad skills is available, such a self-organizing solution to the problem of workflow can be quite efficient. There is no need to plan when a particular agent should execute a particular task, as long as enough agents are available so that a sufficiently skilled one is ready to take over soon after the previous task is finished.

3.4. Aggregation

To fully reap the benefits of synergetic action, we need a final mechanism of coordination: *aggregation*. Different agents contributing different actions at different times to a joint activity will be most effective when the fruits of their activity are assembled into a final product. This process of collecting all the contributions and synthesizing them into a coherent outcome may be called "aggregation" [Surowiecky, 2005]. Like division of labor, aggregation is a parallel process: different streams of activity come together simultaneously. However, while division of labor is a branching process, where an activity is split up into smaller, independently executed tasks, aggregation goes the other way, letting the branches converge again into a single result. Division of labor, workflow and aggregation can be seen as the three fundamental aspects or dimensions of a complex, branching network of mutually dependent processes—as depicted in Fig. 3.

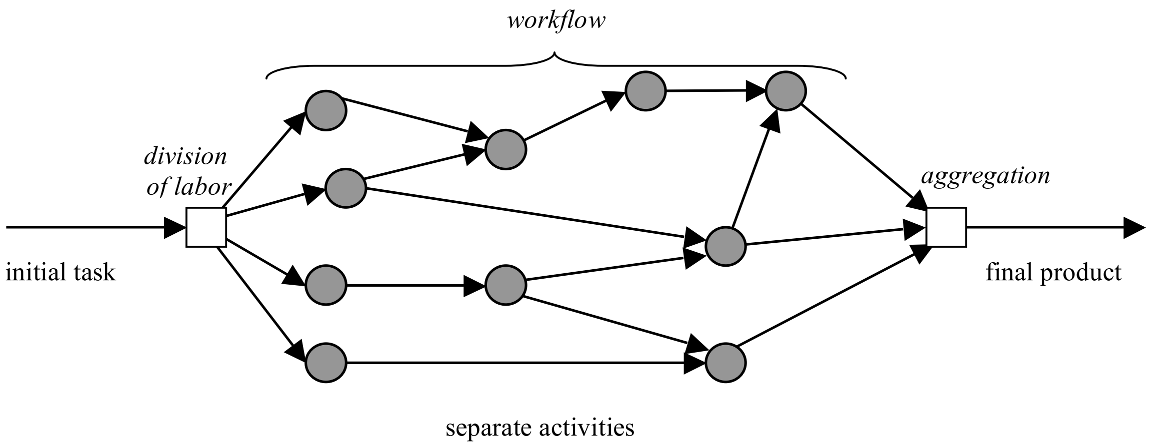

Figure 3: Coordination in which an initial task is split up in separate activities performed by different agents (division of labor), which are followed by other activities (workflow), and whose results are assembled into a final product (aggregation). Grey circles represent individual agents performing activities. Arrows represent the "flow" of work from one agent to the next.

Aggregation too allows for self-organizing approaches. The simplest one is when the different actions superimpose their results on a shared substrate or medium. For example, the work done by the different builders and technicians on a house accumulates in the physical building itself. There is no need to assemble the plumbing with the electrical circuitry as both have been installed on the same walls. But aggregation via a shared medium can also apply to more abstract, informational activities. Again, Wikipedia provides an excellent example: the different contributions to this encyclopedia of global knowledge are aggregated automatically because they are added to the same website [Heylighen, 2007a]. Without this shared electronic medium, assembling the millions of contributions into a coherent whole would have been a task of gigantic proportions.

A similar example can be found in the organization of ant societies. Ants that have found food leave a trace of pheromones on their way back to the nest. In that way, they gradually develop an extensive network of pheromone trails connecting their nest directly to all the surrounding food sources. Discoveries of new sources or shorter routes are automatically aggregated into this collective "external memory", as the different pheromone trails are simply superimposed on the shared physical environment. Paths that are shorter or that lead to richer sources will collect more pheromone relative to less productive paths, so that the network continuously "learns" from the aggregate contributions of the individual ants, becoming ever better [Heylighen, 1999].

A different form of self-organizing aggregation occurs when the products of the different activities can interact and develop links or "bonds", where the one fits in with the other [Heylighen, 2006, 2011]. The examples we discussed before of the spontaneous division of labor in ecosystems or market economies are also examples of spontaneous integration. Businesses or species not only differentiate from other businesses or species in order to better occupy as yet unclaimed niches, they also connect themselves to other businesses or species as providers of resources or services that they need for their own functioning. Thus, a typical business will be a tightly linked hub in a network of suppliers, clients, employees, regulators, and other stakeholders that all depend on each other. Together, they form an integrated socio-economic system that performs a coherent set of functions for society. The mechanism behind this is again variation and selection: agents interact with many other agents. If the interaction is succesful, they will tend to maintain it (selective retention), thus creating a stable bond of mutual dependency. Otherwise, the interaction will be stopped (elimination) and replaced by another one.

4. Collective Intelligence

4.1. *Requirements for Collective Intelligence*

The examples of self-organizing coordination we discussed up to now were mostly based on physical interactions. I now want to focus on purely informational interactions, where the problem to be solved as well as its eventual solution is formulated abstractly, in the form of questions and answers. Solving abstract problems requires intelligence. When this intelligence is localized in a single agent, it may be called individual intelligence. When it is distributed over a group of agents, it may be called *collective intelligence*: it is only the group as a whole that is capable of solving certain problems [Heylighen, 1999]. Collective intelligence assumes that different agents have different forms of expertise (knowledge, information, skills). Otherwise, they would not be able to do more together than individually. Achieving collective intelligence therefore is a problem of cognitive coordination between the different agents. This can again be split up into the four basic mechanisms of alignment, division of labor, workflow and aggregation.

Alignment means that the agents should point at the same targets, so that they do not work at cross-purposes. This implies that agents should agree at least about what the problem is that is to be solved, and about what the different tools or methods are they may need to tackle it collaboratively. However, alignment here does *not* mean that the agents should perform the same actions, because in that case there is no collective intelligence. Adding identical efforts together, like when a number of agents push a heavy weight in the same direction, only makes sense when performing physical tasks, not when processing information. Indeed, when you add a piece of information (e.g. X=3) to the same piece of information (X=3), you still only have a single piece of information. Therefore, a division of labor, in the sense of different agents contributing different information, is essential. Depending on the complexity of the problem, workflow may or may not be needed. Some problems can be solved in a single step, all agents simultaneously contributing their expertise. Others need several iterations, the one building further on the previous one. But the final step of aggregating all the contributions remains essential in order to come to a coherent answer.

Note that this analysis can be seen as a deepening of the analysis of collective intelligence proposed by Surowiecki [2005]. After discussing many examples of successful and less successful cognitive coordination, Surowiecki proposes the following list of requirements that a group must fulfil to exhibit collective intelligence (or *wisdom of crowds*, as he calls it):

- *Diversity*: the more diverse the knowledge and experience possessed by the different members of the group, the more the group as whole knows and the less its members are likely to overlook certain aspects, or to fall prey to the same bias.

- *Independence*: individuals should express their contribution as much as possible independently from other members of the group; otherwise, when the opinion of the one is influenced by the opinion of the other, there is a risk of *premature alignment*, i.e. between the contributions themselves rather than between the targets of the contributions.

- *Decentralization*: this Surowiecky's term for what we have called "division of labor": people should as much as possible be able to gather and process their information in parallel, so that they can together cover an as wide range of aspects as possible.

- *Aggregation*: collective intelligence requires an effective mechanism, such as voting, averaging or discussion, for synthesizing a diversity of individual opinions into a single, collective answer.

4.2. *Groupthink and Polarization*

The most important issue in such collective processes is to avoid Janis what has called "groupthink" [Janis, 1972; for a review, see: Esser, 1998]. This is the phenomenon where people in a group all start to think the same, because a slight initial preference for one approach rather than another becomes amplified via positive feedback. The underlying dynamic is that if someone hears an opinion expressed by someone else, s/he will be more inclined to express a similar opinion. This happens partly because hearing a certain approach will "prime" the mind to consider things from the same perspective, partly because people tend to be conformist, and do not like to contradict or appear to be in conflict with others. The more often similar opinions have been expressed, the less likely group members are to express dissimilar opinions—partly out of conformism, partly because the more they hear a particular position defended, the more they will get convinced that this is the right one, and the less they will be inclined to think of alternatives. In that way, they may all quickly converge to the same opinion, without giving potentially better alternatives the chance to be duly considered.

A more extreme version of this process leads to the phenomenon of *group polarization* (also known as "risky shift"). This refers to the common observation that groups tend to be more extreme in their judgments after a discussion than the members were individually before the discussion [Isenberg, 1986; Sunstein, 2002]. "More extreme" here means deviating more from the middle ground. For example, if jury members are individually inclined to judge a crime relatively harshly (e.g. proposing a 15-year prison sentence on average), after the debates they will tend to judge it even more harshly (e.g. deciding on a 25-year prison term). If a different group is asked to judge the same crime, but the members are individually inclined to be more lenient (e.g. proposing a 10-year sentence on average), as a group they are likely to come to an even more lenient judgment (e.g. a 5-year sentence). Polarization can be explained by the positive feedback underlying alignment, which amplifies deviations: the more people hear arguments for a "risky" position, the more they will think themselves of additional arguments for that position, and the more confident they will become in moving further away from the "safe" middle ground [Isenberg, 1986].

Groupthink is an example of self-organization gone wrong, where non-linear interaction has led to premature alignment on a suboptimal solution, and where the positive contributions of diversity and division of labor have been neglected. Janis [1972] has documented several cases in which meetings of otherwise very knowledgeable individuals succumbed to such groupthink, resulting in catastrophically poor collective decisions (such as the failed "Bay of Pigs" invasion of Cuba by US-supported troops).

4.3. *Avoiding groupthink*

The simplest way to avoid groupthink is to disallow direct communication between the group members, so that the one cannot influence the other one until everyone has been able make a full contribution. However, a collective solution still requires an aggregation mechanism that integrates these different contributions.

This is perhaps easiest to achieve when the looked for solution can be expressed as a number. In that case, everyone can independently make an estimate of the correct number, e.g. by writing it onto a piece of paper. The pieces are then collected, and the final solution is aggregated by calculating the average of the numbers. In many cases, this produces remarkably good results. For example, when at a fair people are asked to estimate the number of beans in a jar, or the weight of a bull, the average of their guesses is typically much more accurate than even the best of the individual guesses [Surowiecki 2006; Heylighen, 1999]. The reason is that each individual guess is biased by the limited experience of that individual, making the estimate either too low or too high. However, when many independent estimates are aggregated, these "errors" or deviations from the optimal solution tend to be "averaged out", because of the law of large numbers. This phenomenon can be demonstrated through agent simulations even for more complex problem solutions [Johnson, 1998], as long as the solution can be expressed as a sequence of numbers that need to be averaged, and as long as the individual agents vary randomly in the errors they make.

However, when different individuals tend to have the same bias (e.g. all overestimating the weight of the bull), their aggregate solution will exhibit that bias too, and the best individual estimate will be more accurate than the average for the group.

The averaging method only works for quantitative decisions. Some of the most common methods, such as discussion in committee meetings, do not obey the criteria of independence and decentralization, and therefore may lead to poor results. The result can be improved if the different members express their opinions independently and anonymously (e.g. on a computer-supported discussion system) before they start responding to the opinions of others, and if the discussion is guided by a neutral moderator, who ensures that everybody duly answers all the important questions, and responds to criticisms of their previous answers. The anonymity makes sure that everybody's ideas are given equal attention (instead of the discussion being dominated by the more authoritative people). This is the basis of the so-called Delphi method [Linstone & Turoff, 1975] that aggregates the ideas of a panel of experts, via several rounds of anonymous, mediated discussion.

5. The self-organization of shared references

In the examples of collective intelligence up to now, we assumed that the participating individuals either are able to communicate their positions to each other, or that there is a mechanism in place that aggregates their contributions. However, group self-organization is also fundamental to the emergence of communication itself.

5.1. *The origin of language*

The evolutionary origin of language is shrouded in mystery, since speech does not leave any traces in the fossil record. The only evidence available about how, when, or why human language emerged is extremely indirect [Christansen & Kirby, 2003]. This includes the use of primitive signaling cries in monkeys [Donaldson et al., 2007], the appearance of symbolism in paleolithic painting and sculpture, and the changes in the anatomical structure of the head and neck that may indicate the evolution of better vocal cords or specialized language centers in the brain. While it may be impossible to pinpoint exactly how primitive humans developed something that resembled modern language, we can get an understanding of the general process via which languages emerge.

Probably the most famous illustration can be found in the work of Steels and his co-workers [Steels, 1998; 2005; Steels & Voght, 1997; Steels & Belpaeme, 2005], who made a series of simulations of the self-organization of the fundamental components of language. The simulations start with a group of software agents or robots (hardware agents) that have to learn to communicate without any a priori shared language. I will here only discuss the simplest simulations, which are focused on the emergence of shared references ("names") for observable phenomena.

An essential requirement for linguistic communication is that the participants should use words or symbols ("signifiers") that refer to the same entities ("signifieds"). A word stands for, represents, or denotes some concept or object that is different from itself. That external phenomenon corresponds to the "meaning" or "signification" of the word. This property of referring or "pointing" to something else is called *intentionality* in philosophy, where it is considered to be an essential characteristic of mind or intelligence [Pierre, 2010]. The concept of intentionality is to be understood so broadly that it applies not only to linguistic, symbolic or cognitive reference, but also to the goal-directedness that is inherent in intentional action. Having an intention means that your (future) action is directed towards a particular target, i.e.

towards a particular situation that you desire to achieve or towards a potential means to achieve it. This is not just a philosophical point: such broad interpretation of referentiality/intentionality is necessary to understand the emergence of language in groups of animals, who do not clearly distinguish between symbolic reference (this signal refers to a predator bird that has been spotted), and goal-directed signalling (this signal means that you need to run for cover). [Donaldson et al., 2007] illustrate in a computer simulation how such "functional reference" systems can self-organize in animals under the influence of natural selection, starting from purely goal-directed ones while gradually becoming more like symbolic ones.

To shift from individual intelligence to collective intelligence, we need to make intentionality collective as well [Heylighen, Heath & Van Overwalle, 2004]. Words and other symbols can only be used for effective communication if the conversation partners understand them in the same way, that is if they agree about wat the word refers to. Developing such shared references is a problem of what we have called *alignment*. We have defined alignment as the unification or merging of the targets of different actions or agents. As long as there is no "director" agent to impose a target on the others, this problem can only be solved through self-organization, that is, spontaneous, reciprocal adaptation of the agents' targets.

The artificial intelligence researchers Luc Steels [1998, 2005] has shown via computer simulations how a group of agents can come to "agree" about the meanings of the symbols they use, i.e. learn to use the same symbols or "names" for the same concepts, via a process of self-organization. The simulation starts with a group of agents, a collection of objects (potential referents) to which the agents can point, and a preliminary lexicon of words or potential names for the objects. Initially, the associations between a name and an object are randomly distributed across the agents, meaning that two agents will in general use different names for the same objects. To achieve alignment, the agents start interacting in pairs of randomly chosen individuals, so that they can learn to mutually adjust their associations.

The basic interaction is called a "naming game": agent X points to an object (e.g. a square), and agent Y formulates a name for this phenomenon (e.g. "bli"), i.e. the symbol that Y would use to represent this phenomenon. X then indicates agreement (if X would use the same name), or disagreement. If there is agreement, the association that exists in both agents' mind between the symbol ("bli") and the referent (square) is strengthened. If there is disagreement, the association is weakened in Y (for whom it was strong), but strengthened in X (for whom it was weak). In that way, after each encounter, the associations for the two agents become a little bit more similar: they have partially "aligned" their relations of reference or intentionality. This game is repeated a large number of times, with different pairs of randomly chosen agents who point to different randomly chosen objects and try to name them.

The general dynamics can be understood in the following way. Each time agent X encounters another agent that uses the name "bli" for the object "cube", X's association between that name and the referent becomes a little stronger, until it is stronger than any other association X has between that name and a different referent. At that moment, X too will start to use the name "bli" for the phenomenon "cube", and thus start reinforcing that association in other agents. Thus, names that happen to appear a little bit more frequently in the initial interactions will rapidly become more "popular", until all agents "agree" on using them. The simulation shows that as the game is repeated, the associations between the various symbols and concepts become more similar for the agents, until they are fully aligned. The result of this self-organizing process is the emergence of a shared vocabulary. This is the foundation for a language that the agents can use to communicate symbolically.

I will not here go into the further simulation research of Steels and his colleagues which illustrates how also other aspects of language, such as semantic categories [Steels & Belpaeme, 2005], phonetics [de Boer 2000ab] and grammar [Steels, 2005], can self-organize out of random interactions. Although the rules that govern the individual interactions may be more complicated for these cases, the fundamental mechanism of mutual alignment that is amplified and propagated via positive feedback remains the same. Instead, I want to briefly review research into the phenomenon of communicative alignment that focuses on real people rather than on computational agents.

5.2. *Conversational alignment*

One disadvantage of working with human beings is that you cannot afford to have hundreds of individuals each interacting thousands of times, as software simulations typically do. Therefore, it is difficult to observe the emergence of a true language within a realistic community. Yet, we can easily study the phenomenon of communicative alignment within a conversation, i.e. a sequence of one-to-one interactions that is limited in time.

Such alignment tends to take place at many different levels [Garrod & Pickering, 2007; Krauss et al, 1995]: intonation, rhythm, lexicon, reference to context [Heylighen & Dewaele, 2002], grammatical structure, etc. The dynamics is always the same: when an individual hears the other partner use a certain pronunciation, expression, reference, or grammatical construction, this will "prime" (i.e. weakly activate or prepare) the cognitive structure that the hearer uses to understand and produce that form of communication [Bock & Griffin, 2000]. Therefore, when the hearer becomes a speaker, (s)he will be slightly more inclined to use the same (or a similar) communicative form. This in turn will make it more likely that the other individual will again use a similar form. Thus, subsequent uses of the form will reinforce each other until the conversation partners converge on always using the same form.

This is the same mechanism of alignment that underlies all self-organization: by reducing the friction that is otherwise caused by the need to recognize and interpret a novel form and because of the high probability of confusion that arises if the conversation partners use different forms, alignment on the same forms makes communication more efficient. As shown by many experiments and observations, one-to-one alignment is a very quick and automatic process that makes conversation much easier than it would be if the partners would have to explicitly agree about how they refer to the different items in their shared context [Garrod & Pickering, 2004].

Conversational alignment will not only produce shared references; it will moreover tend to make those references simpler and more efficient. This has been established in a number of experimental studies of referencing, which examine the process by which people establish a shared perspective during a conversation [Schober & Clark, 1989; Wilkes-Gibbs & Clark, 1992]. In a typical experiment, one person is designated as the "director" and is given the task to describe a number of pictures to a "matcher" who cannot see what the director sees but has to identify the pictures. In order to solve the problem, both participants have to coordinate how they will refer to the pictures. On their first reference to one of the pictures, most directors use a long description, listing detailed pictorial features, in order to make sure that the hearer understands what they are talking about. Then, matchers typically ask questions if the description is not fully clear to them, or confirm that they understood the directions [e.g., Schober & Clark, 1989, p. 216]. Over the course of successive references, as the perspectives of director and hearer become aligned, the description is typically shortened to one or two words, functioning as the shared symbol for the referent. For example, in one of the experiments of [Kraus & Fussell, 1996], the successive descriptions of an abstract shape were: "Looks like a Martini glass with legs on each side", "Martini glass with the legs", "Martini glass shaped thing", "Martini glass", and finally "Martini".

My colleague Frank Van Overwalle and I [Van Overwalle & Heylighen, 2006] managed to reproduce this observation using a simulation based on communication between software agents using a connectionist architecture. After repeated exchanges, the number of features of the situation that were expressed were gradually reduced, until one dominant one was left. This can be understood as another case of friction reduction: as alignment increases, the probability of misunderstanding decreases, and therefore the effort necessary to communicate can be reduced by focusing on the most distinguishing word or expression.

5.3. *Group alignment*

But what about groups consisting of several conversing pairs of people? Will they too converge to one shared reference, like in Steels' "naming game" simulations? According to the experiments of [Garrod, 1998; Garrod & Doherty, 1994], they do. In this type of experiments, two people who cannot see each other have to solve a maze problem together. To achieve that, they must be able to communicate about the different positions in the maze they both see on their computer screens, and the actions that are needed. This assumes that they agree about a particular scheme for naming the elements of the problem (e.g. "go to the third corridor on the right, up from the bottom left corner"). After some back-and-forth describing, questioning, and confirming, like in the Martini-glass experiment, they normally agree about a standard scheme for referencing the different components of the maze.

However, different pairs of people typically settle on different naming schemes. For example, some might start counting positions from the bottom-right, others from the top-left; some might use numbers, others prefer letters or words. In a second stage, each individual is paired with another individual from the same group. Since the two members of the new pair typically have learned different naming schemes in the first stage, they again need to align their references, and agree about a common scheme. When this switching of pairs was repeated several times, Garrod [1998] observed that eventually the whole group settled on a single scheme. This is normally the scheme that happened to be most frequently used in the first stage.

The dynamics here appears to be the same as in the "naming game" simulations of Steels [1998; Steels & Vogt, 1997] and in the general case of self-organizing alignment: small initial advantages for one direction of alignment over the other ones are amplified by positive feedback until that alignment dominates all interactions, thus establishing a shared reference. In the connectionist simulation to which I contributed [Van Overwalle & Heylighen, 2006], the naming game experiment was repeated with somewhat different assumptions about the agents' learning mechanism and mode of communication than the original experiment, but with essentially the same results. This illustrates once again how strong the power of self-organizing alignment is for communicating groups.

6. An experiment in collective intelligence

Establishing a shared system of reference (alignment) is only the first step in collaboratively solving a problem. Moreover, alignment can go too far, in the sense that unusual, but valuable, approaches are suppressed because of the tendency of the largest subgroup to impose its "targets" on the rest of the group. When alignment merely concerns the establishment of lexical conventions or agreed-upon labels, then in essence any label is as good as any other, and alignment is a priori positive. However, when the "targets" of thought and action are fundamentally different, excluding some targets because they represent minority positions will a priori reduce the potential for collective intelligence. Typical experiments in collective problem-solving either artificially impose maximal independence on the individuals (e.g. requiring them to write down their opinion anonymously) until the moment when their contributions are aggregated (e.g. by counting votes or averaging guesses), or allow free-ranging discussion with the intent to come to a consensual decision, thus running the risk of groupthink and a loss of collective intelligence.

Together with my students and colleagues, I have been reflecting about experiments that could provide a more precise but still realistic observation of the emergence of collective intelligence or distributed cognition [Heylighen, Heath & Van Overwalle, 2004].

6.1. *Setting up an experiment*

The first issue was to establish accurate measures for the outcomes of the experiment, and in particular: (1) to what degree was there alignment between the members of the group?; (2) to what degree was the collective solution better (i.e. more intelligent) than their individual proposals? To establish a quantitative measure, I decided to ask questions where the members of the group could express their position on a seven-point scale, going from 1 (completely disagree) via 2, 3 , 4 (agree somewhat), 5 and 6 to 7 (completely agree). To get sufficiently detailed, multidimensional data, I decided to ask at least 20 such questions. This would give me 20 numbers between 1 and 7 for each participant, plus the average for the group. The position of each individual on each of the questions could then be expressed as a list of numbers, e.g. (3, 2, 7, 1, …, 4, 6). In addition to averages, such lists allow us to calculate traditional statistical measures, such as standard deviations and correlation coefficients, that can be used to establish convergence or divergence between opinions.

A more tricky problem is how to quantify collective intelligence: in how far is the group solution "better" than the individual ones? An obvious approach would be to formulate the problem in such a way that it only has a single, unambiguous, quantitative, but not generally known solution, e.g. what is the precise number of inhabitants of Barcelona? The differences between each of the individual or group estimates and the actual number could then be used as a measure of accuracy and thus of intelligence. However, to reach such a quantitative solution, there is not much that individuals can do except offer each their own best estimate. This does not allow much room for the complex processes of self-organizing coordination that this paper has been discussing.

Originally, my intention was to observe and measure the process of achieving a shared conceptualization, where the members of the group would try to align their interpretations of a common, but ambiguous term, such as "fruit", "vegetable" or "sport". Some people may consider chess to be a sport, while others would restrict the term to physical activities such as cycling or swimming. Yet others may use the term only for competitive games, such as football or badminton, while excluding individual activities, such as jogging. To determine people's individual interpretation of the term, I had prepared a list with 20 activities, including the examples above, that may be considered as "sport" to different degrees. For example, all participants agreed that "tennis" is a sport, while no one thought that "solving cross-word puzzles" is a sport. But in between there were a variety of ambiguous cases, such as walking, horse riding, or parachute diving, about which different people had different opinions.

My student, the psychologist Geert Biebaut, converted the list of 20 such activities into a survey, and asked a group of volunteers (students in physical education) to indicate for each of them on a 7-point scale in how far they considere that this activity is a "sport". Initially, each volunteer filled in the survey individually, without contact with the others. In the second stage, they were asked to discuss the question "What is sport?" in group. To keep track of all the arguments put forward, this debate was performed on-line, using an Internet discussion forum. It resulted in an interesting discussion that reviewed various characteristics of sports, such as competition, effort and physicality. After each participant had made at least two contributions, e.g. proposing a better definition, or questioning the contribution of another participant, we let them take the survey again. However, the results were rather disappointing: while some individuals had changed their attitudes in some way, there was no obvious convergence between their opinions, and no clear direction in the shift of opinions. To make sure that this lack of results was not accidental, we repeated the experiment with another group, but the outcome was essentially similar.

The only significant result came from a principal components factor analysis of the different opinion vectors: the most important dimension of variation between the participants before the discussion also appeared to be the main focus of their debate: in how far is competition necessary for an activity to be called "sport"? In other words, from the start there was a clear split in opinion, which fueled the debate, but which did not get resolved. In hindsight, this is not so surprising since the volunteers were students in physical education with a vested interest and long-term experience with the notion of sport, who were unlikely to significantly change their opinion after a single debate. This taught us that a next experiment should focus on an issue where the participants were less likely to have strong preconceived notions. Still, to achieve collective intelligence, they should ideally have a variety of personal experiences to build on, and preferably there should be a criterion to measure in how far the solution they develop is accurate.

As a member of the editorial board of the Journal of Happiness Studies, I had a ready-made subject: what are the conditions for a happy life? There has been a lot of empirical research on this question, performed by psychologists, sociologists and economists [e.g. Veenhoven, 1998; Diener & Biswas-Diener, 2008], that provides us with a basis for a more or less objective judgment. On the other hand, the problem is complex enough that there are different ways to interpret the data, and the research is as yet not very well-known outside a few specialized circles. Yet, happiness is something every individual should have some personal experience with, albeit limited and subjective. My hope was that if a variety of individuals could somehow manage to aggregate these experiences, their collective judgment would be much less limited and subjective. But to measure that, I needed a benchmark that could be considered as an approximately accurate judgment. For this, I could rely on a number of experts in happiness, who were mostly (ex)-colleagues of mine in the editorial board of the Journal of Happiness Studies.

From the literature on happiness, I distilled 20 factors whose correlation with happiness has been researched in some detail. These include obvious conditions such as health or wealth, and less obvious ones, such as IQ, life philosophy, or the degree of trust in other people (see Table 1). These conditions were then turned into survey questions, where the subjects had to indicate on a 7-point scale in how far they considered each condition to be important for achieving happiness. This survey was filled in independently by four experts and by the participants in the experiment, once before and once after their discussion of the subject. To make sure that the results would not be an artefact of a particular method of communication, the experiment was held with three groups discussing in three different ways:

1) in a live meeting that was recorded on video for later analysis;
2) in a "carousel" set-up, in which participants conversed one-to-one for a few minutes, and then switched conversation partners (similar to the Garrod and Steels experiments);
3) via an internet forum.

Conditions of happiness	Avg. before discussion	Avg. after discussion	Average experts
Youth: being young	5.2	3.3	2.5
Status: at least as high as peers	4.6	3.9	4.3
Wealth: being wealthy	5.6	5.3	4.3
Friendship: having good friends	6.7	6.9	5.3
Chance: having good luck rather than bad luck	4.2	4.3	3.5
Peace: absence of military threat	5.3	5.4	5.3
Freedom: living in a free, democratic country	5.8	5.8	5.8
Equality: not being discriminated	5.6	6.0	5.5
Sunny nature: having an optimistic character	6.3	6.0	6.0
Autonomy: having your life in your own hands	6.2	6.7	6.5
Family: having children	4.9	5.3	2.5
Emotional stability: not being anxious or stressed	6.2	5.8	6.8
Intelligence: having a high IQ	4.0	3.2	1.5
Health: not being ill	6.2	7.0	5.3
Education: having a high level of education	5.0	3.7	3.0
Social participation: (sports) clubs, unions, ...	5.0	4.9	4.5
World-view: having a clear philosophy or religion	3.8	4.7	4.5
Relationship: having a stable partner	5.4	5.2	6.0
Safety: low risk of accidents, crime ...	4.7	6.0	6.0
Trust: being able to trust others	5.8	6.6	5.8

Table 1: results of our survey as to which life conditions contribute to happiness, scored on a 7-point scale, from 1 (irrelevant for happiness) to 7 (crucial for happiness). The first colum of numbers lists the average score for one of the experimental groups before they had discussed the issue with each other. The second column lists their average after a live discussion, and the third the average for the experts in happiness research. Note that the "after" score is generally closer to the expert score than the "before" score, even though the participants never received any information about the expert opinion. This seems to indicate the emergence of collective intelligence during the discussion.

6.2. *Results of the experiment*

While the data have not been fully processed yet, this time the results appear statistically and theoretically significant, and surprisingly similar for all three experiments. First, apart from three or four outliers in the scores, the experts appear to agree with each other quite well, and more so than the "naïve" participants. This confirms my assumption that the research on happiness is sufficiently advanced that some degree of "objective" accuracy is possible as to the importance of the different conditions. The average of the expert opinions can therefore be safely used as a benchmark for accuracy.

Second, there is a clear trend towards convergence or alignment: the individual opinions after the discussion are significantly more similar than before the discussion. This was established using three independent measures: (1) standard deviation and (2) entropy of the distribution, which both significantly decreased, and (3) internal consistency ("Cronbach's alpha"), which increased. About the same degree of convergence was observed in all three experimental conditions, albeit a little less clearly in the "carousel" group.

On the other hand, there did not seem to be any polarization, in the sense of opinions becoming more extreme after the discussion. In the present set-up, it seems logical to define the middle ground as the midpoint of the evaluation scale, i.e. the score 4. Polarization then would mean that if the participants scored a particular condition on average as lower than 4 (e.g. 3), then after discussion they would score it even lower (e.g. 2). If they gave it a higher score initially (e.g. 5), they would give it an even higher score (e.g. 6) after the discussion. It is easy to determine whether such polarization took place, by calculating the average difference in deviation from the middle ground between the situations before and after the discussion. It turns out that this difference is about zero (+0.29 in one experiment, i.e. a minimal increase; –0.14 in another, i.e. a minimal decrease).

Finally, and most surprisingly, the average or "collective" opinion after the discussions is significantly closer to the benchmark than the average before the discussions. This was measured using the correlation coefficient between the averages for expert and naïve opinions, which increased from about 0.65 to about 0.76 depending on the experimental condition, with the strongest increase for the live meeting.

This is a clear indication of the emergence of collective intelligence during the discussion: somehow the participants have developed a more accurate understanding of the conditions of happiness not only individually but collectively, and this while avoiding the pitfalls of groupthink and polarization. If this was merely a case of the static aggregation of individual experiences, like in the classic situation where people's estimates of the weight of a bull are averaged [Surowiecki, 2005], then the average opinion before the discussion should have been equally accurate since the discussion did not add any facts that the group as a whole did not know. If their collective judgment has shifted significantly towards the benchmark, this must be because they systematically increased the importance of certain conditions for happiness, and decreased the importance of others. Such a process demands an explanation. Let me propose some initial hypotheses based on the general dynamics of self-organizing coordination that we discussed before.

6.3. *Interpretation of the results*

The simplest explanation for this "shift towards more intelligence" is a process of alignment that would strengthen the initially most common opinions but weaken the others, thus modifying the average position in a non-linear way. This seems unlikely to have happened, because if the majority positions were sufficiently strong and removed from the middle ground, such a type of convergence should normally also have produced polarization. Moreover, according to the notion of groupthink [Janis, 1972], this is unlikely to produce collective intelligence as it would suppress potentially valuable minority experiences. Collective intelligence might still result if the minority opinions were systematically less valuable than the majority opinions: perhaps the minority opinions were those of people who simply lacked experience with a particular condition. For example, someone who has never had problems with his health, may initially consider that condition to be rather unimportant to happiness. Once that person hears that most others have had experience with bad health seriously depressing their happiness, she may shift her opinion so as to increase the importance of health as a factor.

It seems unlikely, though, that majority opinions would tend to be systematically more accurate than minority positions. After all, for several of the conditions, such as youth, living in peace, freedom, or having children, few or none of the participants were likely to have much personal experience about the relative importance of these conditions, as the subjects were mostly young students who did not have children yet, and were living in a peaceful and free country. Therefore, their opinions about these topics appear more likely to reflect common prejudices (e.g. that young people have more fun than old people) than the statistically established facts (e.g. that there is hardly any correlation between age and happiness).

A more likely mechanism here is a spontaneous division of labor and workflow. In a discussion about a variety of conditions, the person most likely to speak out about a particular condition is one who has a lot of experience with that condition. Because of that experience, this individual will be able to argue with a lot of details, conviction, and self-confidence. Therefore, that opinion is likely to have a much bigger impact on the group than the opinion of someone who does not really know much about the specific issue, and who is likely to let others do the talking when that issue is discussed. In that sense, the participants in the discussion are likely each to take on one or more specific roles as the resident expert, say, on "having children" or on "having a life philosophy". For example, assume that one of the participants is a 60-year old mature student, who notes that he is much happier now than when he was young. Such a personal testimony may be enough to shift the others away from the common, but not very strongly held, prejudice that "you must be young to enjoy life".

But, of course, such self-proclaimed authorities can still disagree. That is where self-organizing workflow mechanisms may come in: as long as nobody has clear objections against the ideas that are being proposed, the discussion will proceed smoothly until that issue has been covered, and move on to the next issue. However, if one of the self-appointed "experts" feels that the last speaker has overlooked an important aspect, she is likely to say so, and to add her own experience as evidence for the need to look at the issue differently. For example, she may note that her grandfather always insisted that he was most happy in his youth. This may trigger others to remember what their grandparents used to say about the issue, thus bringing in additional evidence. Self-organizing workflow is precisely this process of one contribution eliciting a subsequent one, which elaborates, complements, or concludes the previous contribution. At the end, the gathered evidence should be more complete and balanced, thus providing a better ground for an accurate judgment. In this example, the conclusion may be that different people experience ageing differently, and that there is not such a clear influence of youth on happiness as the participants initially asssumed. Such a conclusion would bring the discussion participants more in line with the experts, who know from statistical evidence that there indeed is no such clear relationship (see first row of Table 1).

As a last step in our attempt to interpret these results, it may be worth examining why there did not seem to be any groupthink, i.e. the common phenomenon of premature convergence in opinion that reduces collective intelligence. Typical conditions that have been proposed for the emergence of groupthink are direction by an authoritative leader, conformity pressure, and the need to come to a clear-cut consensus [Janis, 1972]. All were absent in the experimental set-up. Since the issue they discussed had 20 different components, it was difficult to come to a clear conclusion. Perhaps most importantly, the participants filled in the survey individually after the discussion. Therefore, there was no pressure, neither explicitly nor implicitly, to "conform" to the opinions of the others, since no one knew exactly what those others had entered in their survey forms. Still, there was some convergence between opinions, but this seems to have been of the "healthy" kind, where participants learned things from each other that were missing from their own limited perspective.

A final note on the mechanism of aggregation in this set-up: this happened partly in each individual's memory, which would accumulate the most salient observations made by others, partly through our procedure of statistical averaging of the collected opinions. The individual aggregation would normally have been more selective and subjective, but because of that perhaps more "intelligent" in singling out the most important contributions. The statistical aggregation, on the other hand, may have to some degree counterbalanced the tendency towards subjectivity by averaging a variety of subjective remembrances. A further analysis of the data may tell us in how far the individual opinions (not just the collective opinion) became more accurate…

In conclusion, the preliminary results of these experiments appear very inspiring for the further study of the self-organization of collective intelligence. The interpretations I have proposed in particular provide concrete illustrations of the dynamics of alignment, division of labor, and workflow. However, to make sure these interpretations are correct, we will need to analyse the results in more depth, in particular by studying the videos and texts of the actual discussions. Moreover, we will need to replicate these results with different experimental set-ups, covering other problem domains than happiness, but where it still possible for the experiences of the participants to converge towards an objectively established "benchmark" solution.

7. Conclusion

This paper has reviewed the mechanism of self-organization, conceived as the spontaneous coordination of actions performed by different agents. Such coordination helps to make the actions more synergetic, while reducing the friction between them. The result is that coordinated actions achieve their intended goals more easily and more effectively. In particular, coordination may result in an apparently unreachable goal or unsolvable problem getting within reach, as sources of obstruction vanish and missing elements are fitted in.

The underlying dynamic of self-organization is local trial-and-error or variation-and-selection, in which two interacting agents try to mutually adapt their actions, until they hit on a "coordinated" pattern that is acceptable to both, and thus is selectively retained. This local pattern is then typically propagated step-by-step to the neighboring agents and the neighbors' neighbors. The spreading "wave" of coordination is thus amplified until it encompasses the global system, via a process of positive feedback.

Coordination can be decomposed into four relatively independent mechanisms: alignment, division of labor, workflow and aggregation. Alignment is the simplest, as it merely requires the agents to "point in the same direction", i.e. direct their actions at the same targets. This is necessary to avoid the friction that is otherwise caused by opposing actions. Alignment creates convergence or homogeneity between interacting agents. When the agents are distributed across space, the resulting homogeneity may be limited to a certain region, with boundaries between differently aligned regions emerging after self-organization. This can explain the appearance of separate cultures or languages, and the points of friction between them.

Even when such remaining friction is avoided, alignment is not yet sufficient to reap the full benefits of synergy, in which the whole of the actions produces more than the sum of the effects produced by each action separately. Synergy requires complementarity, in which one action makes up for what the other one lacks, so that together they can achieve goals that they cannot achieve alone. Synergy is promoted by the other three coordination mechanism. Division of labor means that different agents perform different actions at the same time, so that each can contribute its unique expertise to the part of problem it is most skilled at. Workflow means that an action is followed by a subsequent action that fills in the gaps left by the previous one. Aggregation, finally, ensures that all these different contributions are assembled into a coherent outcome.

These mechanism have been defined at the most general, abstract level, so that they can in principle be applied to any complex system. Indeed, all systems and their components can be conceptualized as agents, i.e. entities that act in response to sensed conditions, and this with apparent "intentionality"—meaning that these actions are directed at a particular target or goal. However, the present paper has focused on applications in social systems, where groups of human individuals communicate with each other.

The first issue here is the emergence of *collective intentionality*: how do groups align the targets of their communications and actions? In the domain of language, this problem has been investigated by means of a variety of software simulations and experiments with groups or pairs of conversing individuals. The basic mechanism is that each time an agent targets a particular referent or communicative structure in its interaction with another agent, this primes (weakly prepares) the second agent to target a similar referent, making a shift towards a common referent slightly easier. Many such small, individual shifts eventually snowball into the emergence of a reference shared by the whole group. This research confirms and illustrates the general mechanism of self-organizing alignment, while clarifying the origin of linguistic conventions.

A second issue is the emergence of *collective intelligence*: in how far do people manage to solve problems better as a group than individually? Most research in this domain has focused on the problems of *groupthink* and *polarization*, a form of premature alignment in which valuable contributions are suppressed because of a tendency of groups to conform to and reinforce any emerging consensus. This results in phenomena of "collective stupidity" or "madness of crowds", rather than "collective intelligence" or "wisdom of crowds". The general recommendation [Surowiecky, 2005] therefore has been to minimize the (non-linear) interactions between individuals that promote alignment, and to use some neutral mechanism such as averaging to directly aggregate the individual contributions. While this strategy is undoubtedly useful in a number of cases, it risks to throw the baby out with the bathwater, as it makes self-organizing division of labor and especially workflow more difficult.

To investigate these issues, I have designed a number of psychological experiments in which a group of people discusses a complex question. In the second group of experiments the question ("what are the conditions for happiness?") was chosen in such a way that each participant had some limited, subjective experience with it, but a group of experts was available to provide a more balanced, objective estimate. The average judgment of the experts was used as a benchmark to measure the quality or accuracy of the different outcomes. The experiment was performed with three groups, each using a different form of communication. After each discussion the opinions of the participants had become more aligned, but not polarized, while moving significantly closer to the benchmark. A plausible interpretation is that spontaneous division of labor and workflow elicited synergy, and therefore collective intelligence, while the absence of any pressure to conform prevented groupthink. These results are as yet still preliminary, but they seem sufficiently solid to warrant further experiments in the same vein.

In conclusion, self-organization in communicating groups is a fascinating topic that can throw a new light on a variety of fundamental problems, including the origin of language and communication, how best to achieve coordination between agents and their actions, and how to maximize the intelligence of collectives. Both the conceptual framework and the methods for experimentation and simulation appear sufficiently developed to enable quick further progress. I therefore hope this paper will encourage other researchers to further investigate these issues.

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