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DISTRIBUTED INTELLIGENCE OF MULTI-AGENT SYSTEMS. PART II: Collective Intelligence of Social Systems

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Abstract. Part II of the multi-part survey is devoted to the features and empirical characteristics of distributed intelligence (DI) as the capability of a collective agent (social system) to perceive, process, and use new information in order to achieve its goals. The implementations of DI in human social systems are considered: the crowd wisdom of unstructured communities and the collective intelligence of small groups, organizational systems (OSs), and big systems (states, peoples, and civilizations in historical time). Unlike the swarm intelligence of social insects and animals, collective intelligence in human communities is built up of individuals capable of deep information processing and creative activity. The tight links between the DI of human organizational and social systems and individual human intelligence are emphasized. The increasing contribution of AI to modern collective intelligence is illustrated by flexible resource management in real time. The factors determining the effectiveness of the DI of a multi-agent system are identified as follows: (a) the cognitive capabilities of individuals, (b) the structure of interactions between them, (c) collective goal-setting, (d) external information recording, compression, and processing, and (e) creation of new "images" of the environment and oneself in it. A modular perception model of external influences by an intellectual agent is discussed.

Keywords: multi-agent social systems, collective intelligence, groups, organizational systems, big systems, modular model of perception.

INTRODUCTION

The analysis of human intellectual activity and its mathematical and technical modeling are the main directions of cognitive psychology, information technology, cybernetics, robotics, and other sciences [1]. These disciplines have established key features common to *human intelligence* (HI), the elements of animal intellectual activity, and the computer implementations of *artificial intelligence* (AI) and *distributed intelligence* (DI) of multi-agent systems. The key features are as follows: the autonomy of agents, including collective ones; information perception (the "reflection" of external influences), processing, and generalization (compression); learnability; the use of information to achieve the agent's objective goals in a variable environment; and several more specific features. DI research includes the study and modeling of cooperative effects in various multi-agent systems: biological, social, economic, and organizational, as well as in groups of autonomous technical devices.

Collective information processing and its use by social systems consisting of people include the dynamics of pedestrian and automobile traffic flows [2, 3], economic activity, stock market, the interaction of organizational systems (OSs), the combat operations of military units, participation of political parties in election campaigns, and many other processes [4–6]. This multi-part survey considers the main kinds of DI known to date in systems of interconnected agents, including biological, technical, social, and organizational ones. Part I, see [7], was devoted to the simple forms of DI without conscious information processing by individuals: the swarm intelligence of social insects [8], flocks of birds and fish schools [9], and groups of interconnected robots [4, 10]. Also, the features of information perception and processing in "proto-intelligent" automatic control schemes [11, 12], the most widespread implementations of AI were briefly described (artificial neural networks [13], logical intelligence [14], and some swarm intelligence simulation methods for *nature-inspired algorithms* [15]). According to part I of the survey, the DI of multi-agent systems is not reducible to standard schemes of individual or collective decision-making or hierarchical or network control: it represents an independent and insufficiently studied aspect of cooperative dynamics [16] that involves elements of the chaotic behavior of agents.

Part II of the survey considers some forms of the collective intelligence of multi-agent social systems (MASSs) consisting of people. Unlike the simpler kinds of DI, the elements of such systems are capable of deep information processing and creative activity, which is reflected by the formal description of their dynamics by game-theoretic methods. Another feature of these systems is the close interaction of individual and collective forms of intelligence, with the gradually growing role of AI in recent decades. Based on the material presented below, we introduce a general classification for all known forms of intelligence and outline a way to its meaningful mathematical description.

1. COLLECTIVE INTELLIGENCE IN HUMAN COMMUNITIES

1.1. The Wisdom of Crowds

The swarm intelligence of biological individuals can be associated with *crowd wisdom* in human society or the DI of an unstructured community of people. Sociologists and philosophers of the 19th–20th centuries (G. Le Bon [17], H. Ortega y Gasset [18], and others) emphasized the reduction of individual consciousness in the human mass as well as the primitiveness and manipulability of the crowd's collective behavior. In the 21st century, following F. Galton's sociological study[1] [19] (a century ahead of modernity), the interest of researchers was attracted by the ability of human MASSs to process external information and the mechanisms of cooperative actions based on it.

In contrast to the conscious elaboration of opinions in groups (see below), crowd wisdom manifests itself as a spontaneous process possibly not affecting the cognitive functions of individuals. For example, a large crowd bypasses an obstacle that is invisible to most of the people moving in it (Fig. 1). The motion mechanism in a crowd of pedestrians—following neighbors and avoiding collisions—is unified for communities of biological individuals and formations of drones [10]. The manifestations of DI in pedestrian traffic flows were considered in several works [2, 4, 16]; they were systematically analyzed by D. Helbing et al. [21]. Sociological studies and mathematical modeling are synthesized in the field of *crowd (mob) control* with numerous tasks to ensure the safety of mass events [22, 23] and suppress their manipulation [24].

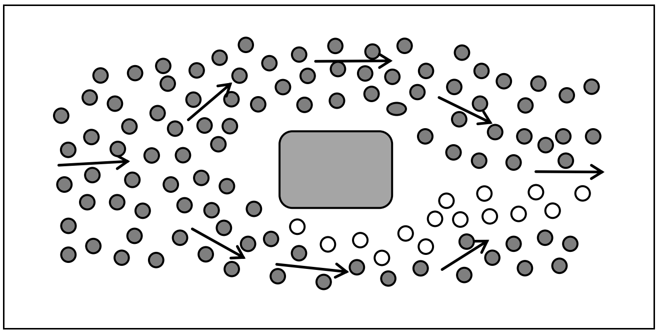

Fig. 1. An obstacle bypassed by a moving crowd.

The analogies with swarm intelligence in unstructured human communities extend to economic relations, including the Invisible Hand of the market and the stock market, where the desire of agents to maximize profits is transformed into a collective evaluation of assets. The highly politicized assertion about the market as the best mechanism for processing economic information is widely presented in textbooks on neoclassical economics [25]. Manifestations of the wisdom of the stock market were discussed in the book [6], although (in our point of view) without any convincing examples. The postulated efficiency of the DI of bidders is utilized by *political markets*, where predictions of political events can be purchased and sold up to their occurrence similar to futures contracts; by assumption, the price of a forecast reflects its quality [26]. Since reliable pricing models in the stock market are still unknown, "market forecasts," becoming widespread in recent years, can be used to manipulate public opinion.

Nowadays, information exchange on the Internet is often treated as an implementation of distributed intel-

[1] The paper [19], quoted at length in the book [6], discussed the distribution of bull's slaughter weight estimates provided by 787 respondents at an agricultural exhibition in Plymouth. An incentive for accurate estimates (which required specialized knowledge) was given out of the money from selling respondent cards at 6 pennies apiece. The median of all estimates (1207 pounds) exceeded the actual slaughter weight of the animal (1198 pounds) by only 0.8%. The large-scale Internet surveys recently conducted by researchers from Stanford University (2000 participants, 1000 questions in 50 different knowledge domains, and about 500 000 answers) [20] confirmed the higher efficiency of "average" intelligence compared to the majority of individual respondents and the strong effect of collective opinion (when it was reported to participants at the intermediate stage of the experiment), which *worsened* the final result.

ligence [27]. The operation of search engines is a simple and convincing example of crowdsourcing that engages the DI of network users in the analysis of large datasets. In response to a user query, a search engine ranks the hyperlinks to websites in descending order of the number of previous references to these sites. This scheme, first implemented by the Google PageRank search engine in 1998, is currently used by all major search tools on the Internet. The direct network analog of marking ant paths with pheromone is very effective: the list of found sources, which may contain hundreds and thousands of entries, is usually headed by the most relevant and interesting ones. Processes in network structures are often discussed in terms of swarm intelligence [28].

1.2. Opinion Dynamics in Groups

At first glance, the problems of optimal operation of MASSs in human society, where communication and conscious actions play an important role, are far from the dynamics of a school of fish or the life of a bee hive. Nevertheless, they also manifest the general operating principles of DI: connections between system elements, information transfer, and an objective goal pursued by the system that does not necessarily coincide with the goals of its elements. (Some examples are staff reduction in an organization, military operations, etc.) The objects calculated in mathematical models of such systems—plans, opinions, and strategies—are the products of both individual and collective mental activity, e.g., street traffic planning considering the weather forecast. General methods for solving problems of this level of complexity have not been fully developed so far; only the most common partial schemes and heuristics can be discussed here.

The simplest “molecular” form of MASSs in human communities is a *small group* where all individuals (agents) are aware of all other members of the group but differ in the strength and direction of interactions (*influences*): a philatelist club, an enterprise’s board of directors, an army platoon, etc. The mutual influence in a small group, which determines its dynamics, is reflected by the arcs of a weighted digraph, whose vertices correspond to the agents [29]. This approach formalizes the contributions of individuals to the collective dynamics of the group, even if their actions are variable and imprecisely known. A complete graph describes an unstructured group where each agent interacts equally with the others.

Opinion exchange and the development of a common position are the main content of the activity of expert councils; in one form or another, they are present in the work of most governing bodies and authorities. Modeling various aspects of this process includes the dynamics of reaching a unified opinion (consensus) and assessing the degree of influence of group members on the resulting decision. At the same time, the well-known ability of a group to propose a new non-standard solution to a problem or to find an adequate response to unforeseen changes in the situation is extremely difficult to formalize and is usually not reproduced in models.

DeGroot’s model [30] is a mathematical foundation for reaching consensus. In this model, the mutual influence of agents is reflected by a stochastic *influence matrix* $W = ||w_{ij}||$ with nonnegative elements $\left(\sum_{j=1}^{n} w_{ij} = 1\right)$. The non-diagonal elements of the matrix W correspond to the mutual influence of different agents ($i \to j$ when $w_{ij} > 0$) whereas the diagonal elements to self-influence (the stability of the agent’s position). The opinion vector of n agents, $\mathbf{x}(t) = (x_1^{(t)}, x_2^{(t)}, \ldots, x_n^{(t)})$, evolve over discrete time t in accordance with the iterative procedure

$$\mathbf{x}(t+1) = W\mathbf{x}((t)). \tag{1}$$

If the mutual influence graph of agents has a tree subgraph in which all vertices are reachable from a single root vertex (i.e., there is an agent directly or indirectly influencing the opinions of all other agents), then the opinion vector in (1) converges to a consensus $\mathbf{x}^*$ [31]:

$$W\mathbf{x}^*(\infty) = \mathbf{x}^*(\infty).$$

The consensus vector is calculated as the eigenvector of the matrix W corresponding to the eigenvalues $\lambda = 1$.

DeGroot’s model can be applied to predict the contribution of real persons to the elaboration of decisions of a group (the top management of a competing firm, the board of the defense ministry of a probable enemy, etc.). For this purpose, it is necessary to determine the elements of the matrix W by expertise [29]. In *sparse* influence matrices, many elements (including those without available expert assessments) are assumed to be 0, which additionally complicates the calculations.

DeGroot’s model has been developed in thousands of publications over the last decades; for example, see [31]. A simplified consensus search procedure is based on the heuristic *bounded confidence* algorithm, which reproduces the convergence of the parties’ positions during the discussion [32]. In this algorithm, agents’ opinions are described by a continuous parameter $x_i \in [0, 1]$. Consider a pair of agents in neighbor vertices of the graph reflecting the structure of interactions in the group; their positions (x_i, x_j) converge to one another if the difference between them does not exceed a given *confidence threshold*:

$$\Delta x_{ij} = \left| x_i - x_j \right| < \delta.$$

In this case, at each subsequent modeling step with $x_i > x_j$,

$$x_i(t+1) = x_i(t) - \mu \, \Delta \, x_{ij} \, ,$$

$$x_j(t+1) = x_j(t) + \mu \, \Delta \, x_{ij} \, ,$$

where $\mu \in [0, 1]$ is the convergence parameter. If $|x_i - x_j| > \delta$, the agents' opinions remain invariable. This can polarize the opinions, dividing the group into fractions (Fig. 2).

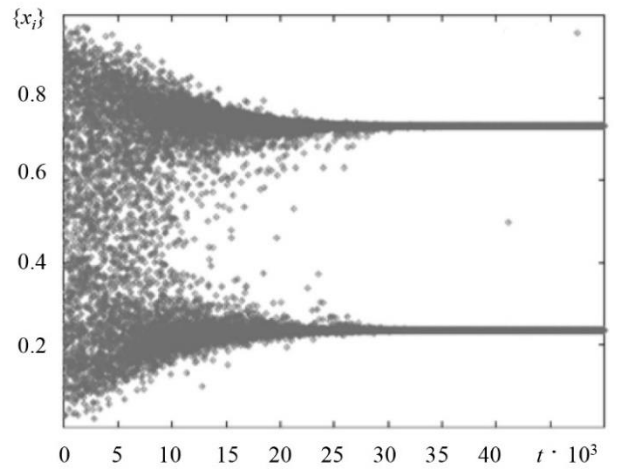

Fig. 2. An unstructured group of agents divided by the continuous opinion parameter $x \in [0, 1]$ into the fractions $x = 0.25$ and $x = 0.75$ under the agreement threshold $\delta = 0.2$ in the bounded confidence model [32].

The bounded confidence algorithm with coefficients reflecting different weights of opinions (e.g., those of a minister and his or her deputies) determines the agents' contributions to the common position, but it also critically depends on the adequacy of expert assessments and the model parameters. A variety of empirical mutual influence schemes have been proposed and used to date; in particular, they are used to analyze opinion formation and propagation in social networks (see the publications [33, 34], part III of the survey [22], and the overviewing chapter [31] in the book [12]). Practical methods for reaching consensus are discussed in the scientific and educational literature [35, 36], including the works explicitly aimed at manipulating public opinion on the issues of "anthropogenic" global warming [37].

Mutual influence schemes for reaching consensus in a group with an initially given set of opinions allow for no fundamentally new solution: they do not reproduce a key property of DI, more often called *collective intelligence* for groups and other relatively regulated human systems. At the same time, computerized decision support systems (DSSs) for collectively elaborating unknown solutions of a problem, including *brainstorming* [38, 39], employ practical group-based recipes for creating new information similar to inventive heuristics [40]: "loosening" the modifiable model, encouraging random associations, and actively expressing any ideas that become common knowledge (see the blackboard of the bee colony algorithm discussed in part I of the survey [7, 41]). We emphasize that successful nonstandard problem-solving by a group is not reduced to the insight of one discussion participant: the new idea must be approved (and usually corrected) by other participants under the guidance of moderators. Thus, brainstorming corresponds to collective creativity, a process that has not been mathematically formalized so far.

Stochastic disturbances of the "states of mind" of individuals participating in a brainstorming session (or, e.g., in a professional scientific seminar) inevitably cause erroneous assumptions and other "noisy" information. But exactly this process facilitates the emergence of insight among the participants. Its results are consolidated by the collective using a mechanism similar to the effect of temporary leaders in a moving flock of birds (see Fig. 6 in part I of the survey [7]): a promising assumption is discussed, criticized, and modified by other discussion participants. Another feature of brainstorming is the enlarged "library of knowledge" due to the different areas of expertise of the participants[2] (similar to the expanded field of view of a school of fish [7]).

The verification of emerging ideas in the general discussion and their consolidation in the individual consciousness of each participant correspond to the creation of new information by the emergent collective intelligence of the group. Another implementation of this approach is *e-expertise*, which also yields nonstandard solutions [42]. The obvious parallels of this process with the manifestations of swarm intelligence in simpler biological communities (see part I of the survey [7]) reflect a single mechanism for implementing group DI that exceeds the individual capabilities of group members.

Despite the fundamental difference between the cognitive abilities of humans and swarm animals, analogies of "creative" intellectual activity of groups with swarm intelligence have been noted many times in the literature [43]. Nevertheless, in its formal models, devising new things is usually postulated as an

[2] We underline again that the terms "*knowledge*" and "*competence*" are used here in their "naïve" and intuitive clear everyday meaning.

empirically observed effect. The methodologies of creative complex activity were overviewed in the book [44] together with mathematical models for developing, mastering, and using new technologies.

1.3. DI of Organizational Systems

The transition from the swarm intelligence of unstructured communities to the collective intelligence of groups, where mutual influence is ordered[3], is accompanied by increasing the accuracy and depth of proposals. Even more ordered *organizational systems* (OSs) are comparable to individual human intelligence in the efficiency of routine information processing; they are often treated as a "bureaucratic machine" under some personal leadership. Similar to the explanation of new discussion results by the individual insight of one participant, this representation is not quite true. For example, the amount of information in an annual report of the enterprise staff goes far beyond the knowledge domain and interests of each coauthor, is addressed to several different groups of experts (technicians, financiers, lawyers, etc.), and is only corrected by the OS top management (hereinafter called the Principal). The information is then collectively processed by the superior organization and leads to organizational measures, e.g., changes in the annual funding. Thus, the DIs of various OSs establish a direct dialog, where the individual intelligence of their elements plays a subordinate role.

Unlike a group, where influence graphs can be arbitrary, organizational systems have a rigid, usually hierarchical architecture (Fig. 3) and are controlled by a single Principal (an individual or a group, e.g., a board of directors). Control actions (red solid arrows in Fig. 3) propagate in the system top-to-bottom to the lower levels of the hierarchy (finally, to direct executors); operational information is transmitted in the opposite direction (blue dashed arrows). By the presence of hierarchy, an OS resembles an inverted artificial neural network (ANN). This similarity is reinforced by the possibility of increasing the connectivity of each layer's node using the indirect influence of the system elements on any departments through the information transmitted to the Principal.

While ANN nodes only amplify or weaken signals of the previous layer, individuals in an OS are capable of deep information processing and creative intellectual activity. In addition to the system structure, their operation in the system is formalized by job descriptions, analogs of activation functions ("filters") in ANNs. Note that collective decisions (in the form of Principal's orders after receiving operational information) are usually made in a non-routine and variable environment. The activity of an OS, well known from everyday reality, certainly includes the reflection of the current situation (reports), information compression (integrated indices), goal-setting, learnability and adaptability, as well as the generation of new knowledge (schemes to fulfill plans, upgrading, response to emergencies, etc.), i.e., all the features of intelligence mentioned above. Information processing and its use in OS dynamics testify to DI in this type of multi-agent systems, but no generally accepted theory has been developed in the modern literature so far.

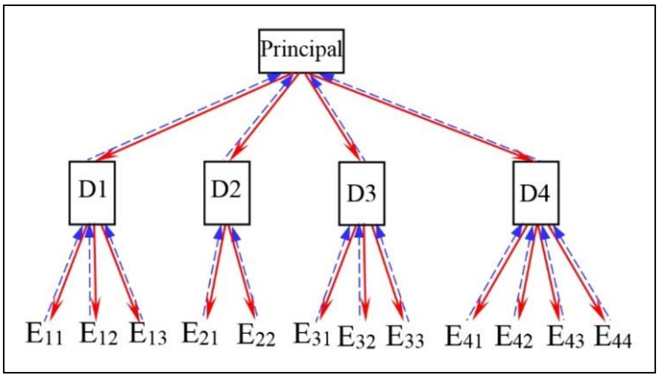

Fig. 3. A structural diagram of an organizational system: D—departments and E—executors.

Usually, the operation of OSs is formally described in terms of *game theory*. As a rule, such descriptions consider the interaction of absolutely rational [45] agents, in which the payoffs of each agent generally depend on the actions or strategies of all agents. (One exception is the models of bounded rationality [46].) The main challenge of game theory is to predict the result of agents' interaction as an equilibrium of their game: a vector of their actions (strategies) that is stable in some sense. Thus, agents in game theory are intelligent by definition (on the one hand) and are kept by game rules (the requirements of rational behavior) within much more rigid bounds than in real multi-agent systems (on the other hand).

In particular, a fruitful direction of this field is *the theory of active systems* (TAS), a branch of control theory for organizational systems whose dynamics are affected by the intelligent behavior (*activity*) of system participants [47]. Several control methods and mechanisms have been developed within TAS for systems containing active elements with their own goal functions. (Pursuing their own interests, such elements can degrade system operation, e.g., by distorting the information transmitted.) Non-manipulable (strategy-proof) mechanisms have been designed for control, resource allocation, motivation, and other tasks in

[3] Computer support aids of a brainstorming session or, e.g., a scientific seminar in an online format structure the group of participants and organize the discussion process.

models of active systems. In particular, *the fair play principle* (the principle of incentive compatibility) allows maximizing the Principal's goal function on the set of plans corresponding to the maxima of the goal functions of active agents [47, 48]. Such branches of game theory as contract theory and *Mechanism Design* (MD) deal with similar problems; see a comparative review of the results of TAC and MD in [49].

Hierarchical [50] and reflexive games [51] are also used to describe OSs. In a normal form game Γ_0, all agents choose their strategies once, simultaneously, and independently of each other. In a *hierarchical game* Γ_i, contrasting with the game Γ_0, a Principal chooses a strategy x_1 first (the game Γ_1) or informs the second (subordinate) player(s) of the response to the strategy chosen by the latter (the game Γ_3), and so on in the ascending chain. That is, $x_j = f(x_i(x_j(x_i')...))$, where x_2 denotes the strategy (move) of the second player, and the moves of players x_j', x_j'', x_j''' (j = 1, 2) at different planning levels in the function f may differ.[4] Multilevel structure is also inherent in *reflexive games* [51, 52], where agents have partial awareness of the strategy sets of their opponents and the latter's awareness of the agent's own strategies. (In classical games, the strategies of all players are common knowledge.) In the graph representation of a reflexive game, the vertices $\{x_i\}$ expressing the agents' strategies are supplemented by the vertices $\{x_{ij}^{(n)}\}$ of phantom agents, where x_{ij} is the strategy of agent j in the belief of agent i and n gives the level (rank) of reflexion. Within this approach, the comparative intelligence levels of agents are expressed by the number of reflexion ranks available to them. Adding vertices to the MASS structure obviously complicates the game description and, consequently, equilibrium search based on it.

In OSs of a more complex structure, considering interactions between same-level agents leads to nested games with the competition of executors and independent Principals (in this case, described by games Γ_0, see Fig. 4). Such games correspond to active systems with coalitions of agents and MASS control by competing Principals, with numerous applications in information confrontation and crowd (mob) control [24, 33]. Game-theoretic methods in OS control were discussed in detail in the book [53].

Multicriteria *complex assessment* mechanisms have been designed for the objective monitoring of the results of active systems, which is required for planning and control actions [54]. This information concentration method in hierarchical OSs is similar in its function to the training procedures of convolutional ANNs. Analogies of information processing in neural networks and in hierarchical organizational systems were considered in [55].

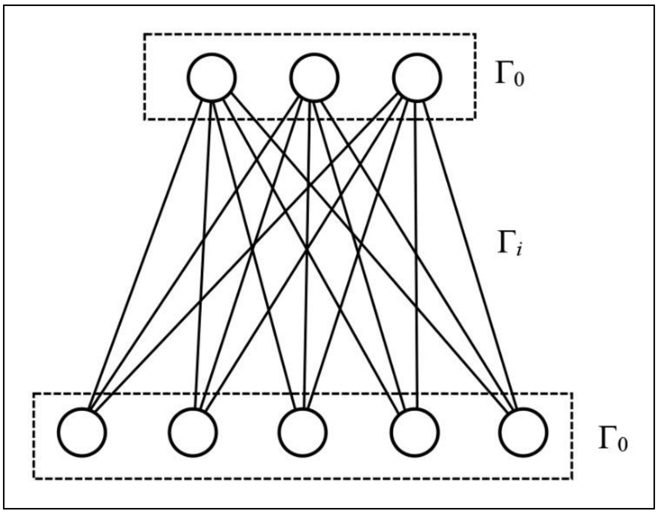

Fig. 4. The nested structure of the game $\Gamma_0(\Gamma_i(\Gamma_0))$ [52].

The formalism of game theory allows analyzing and predicting the actions of intelligent agents, as well as forecasting their outcomes (equilibria), but the set of possible actions must be fixed in the problem statement. Models based on the game-theoretic description of an OS, like formal opinion dynamics algorithms in a group, do not cover emergent events, i.e., fundamental changes in strategies (act of bankruptcy, development of an anti-crisis program, etc.). New knowledge generation by a system of interconnected individuals, empirically well-known, strikingly differs from consensus models as a choice of the best individual program of action or a weighted average of several predetermined programs.

In some sociological models, moods and morale in real collectives and groups are considered by introducing stylized "humanitarian" variables: the level of trust, mutual assistance, etc. [29]. Indirectly reflecting the presence of DI in OSs, this approach also does not reproduce its operation mechanisms since the results of collective information processing appear to be predetermined.

Analogies with this situation can be found in studies of the causes of altruistic behavior in MASSs of biological (i.e., inherently selfish) individuals [56, 57]. Game-theoretic models confirm the advantages of communities with altruistic agents whose equilibrium share depends on external conditions [58], but they do not reproduce the emergence mechanism of such

[4] The addition of feedback loops complicating the function f is limited by *Germeier's theorem* [50, 52]: the Principal's maximal guaranteed payoff in games Γ_m with an even (odd) number m does not exceed that in the game Γ_2 (Γ_3, respectively).

agents: altruism has to be postulated [56]. Thus, game theory describes the manifestations of DI in OSs only phenomenologically. At the same time, the emergence of altruism in an "intelligent" MASS is explained at the qualitative level by the objective goal of self-preservation of the system and the variability of agents' behavior as a useful feature fixed by biological evolution or (and) learning.

1.4. Emergent Intelligence in Resource Management Systems

The intermediate position between standard OSs, usually involving from several tens to several thousands of individuals, and the DI of macroscopic systems (see the next subsection) is occupied by *emergent intelligence* (EI), a special form of AI in transportation, logistics, economic, and combined management systems of enterprises at the municipal or industrial level (see [59] and other books in this series, as well as [60]). An intelligence feature of such systems is the ability to allocate limited resources in a changing environment without direct operator intervention. The number of varying parameters in such problems makes rigid centralized control, if it is possible at all, critically dependent on computer power and complicates the correction of random disturbances in real time due to breakdowns, failures, weather conditions, etc.

An alternative to direct centralized control and optimization is mathematical models of flexible systems with information exchange among agents (the suppliers and consumers of resources or services). The *Belief–Desire–Intention* (BDI) model proposed in the 1990s, in which agents are initially intelligent and their interactions are defined by mathematical logic, has encountered difficulties in the formal definition of basic functions of intelligence and software implementation [61]. As it has turned out, a much more promising model is a system of "boundedly intelligent" agents with the algorithmically defined aspiration to maximize an objective function (*virtual money*): using the known values of payoffs and losses, these agents establish and switch connections between the sets of suppliers and consumers in a variable environment. In such models, a real-time *intelligent resource management* system is built based on the dynamic *network of needs and opportunities* [62].

The emergent intelligence of multi-agent resource exchange models exhibits all the main features of DI: variable dynamics of interconnected supplier and consumer agents, model information exchange between them in the form of redistributing supply and demand volumes, agents' striving for maximum individual payoffs, and evolution of the system (represented by a *dispatching* agent) to maximize the general goal function. The representative paper [63] briefly overviewed the state-of-the-art in this area and presented a smart ecosystem model minimizing the difference between demands and available resources under external disturbances.

The metaheuristic of "market" agents (see NIMs in subsection 3.3 of part I of the survey [7]), which seek to maximize the payoff by redistributing themselves among the most profitable "orders," has been effective in a wide range of applications [62]. The number of research works in the field of EI has been growing over the last decade [64], particularly reflecting the popularity of new terminology in the traditional problem of planning and operational resource reallocation (see [1]). The introduction of computer AI into the distributed intelligence of a social system is very evident here.

1.5. DI of "Macroscopic" Systems

Macroscopic systems in physics include sets of interacting particles whose number $N \sim 10^{20}–10^{24}$ can be only a few orders of magnitude smaller than Avogadro's number $6.02 \cdot 10^{23}$. Brownian particles containing $10^{12}–10^{15}$ atomic and molecular subunits already belong to mesoscopic systems. In this sense, all social systems are either micro- or mesoscopic; this explains well the large-scale fluctuations of their parameters. However, in human society, "macroscopic," or *large*, systems are MASSs containing tens of thousands or more individual agents. Such systems—countries, peoples, economic sectors, etc.—usually have a complex and weakly ordered structure and an incompletely studied operation mechanism with a strong effect of random factors.

The phenomenological description of human society consisting of collectives as "generalized persons" and the projections of physical laws onto the social environment were systematically presented, apparently for the first time, by V.M. Bekhterev in his book [65], which was far ahead of its time. The dynamics of large social systems are still predominantly analyzed at the qualitative level in the humanities.

The hypothetical *Global Brain* of computer users united on the Internet [66] can be considered the ultimate representative of macroscopic DI. However, the declared analogies of this dynamic network with neural networks of the brain [67], stated only at the verbal level, look doubtful from the point of view of the connection of functions with the structure (for the Internet, it seems chaotic without a control center) and hardly indicate its cognitive capabilities (see Section 2). The coordination of elements and the birth of new knowledge in macroscopic subsystems of the modern world (transportation, scientific, and commercial ones) were described in Surowiecky's book [6], a popular introduction to the range of DI problems.

From a general point of view, the ability of large systems to process information and act accordingly is beyond doubt, but the DI of such systems has been described only at the qualitative level in the literature. At this level, it is possible to identify its key characteristics consistent with manifestations of other forms of collective intelligence:

• the disordered interactions of collective actors, with competitive (economy, scientific and technical environment, and domestic policy) and antagonistic relations (foreign policy, wars) prevailing;

• no features of personal governance (in particular, weakened ethical standards);

• systems tending to equilibrium;

• biosimilar life cycles.

An unexpected feature of the DI of large human systems is often a low level of information processing and solving specific current tasks compared to individual human norms. Like the reduction of ethics, this is due to the non-personal mechanism of cooperative thinking and a weakly ordered structure of inter-agent interactions. The decreasing role of ethical norms in large-scale collective intelligence, up to their temporary abolition (wars), is caused both by the size of large systems (the relative value of a single agent becomes insignificant against their background) and by the long (centuries-scale) time of their existence. The latter circumstance explains the low efficiency of large intelligence in solving immediate problems: the DI of large systems solves problems on a different time scale.

A large field of *biopolitics* [69] is based on analogies between the behavior of political actors and animals [68]; parallels between the collective actions of animals and humans are also considered in *human ethology* [70]. Another characteristic feature of this kind of DI is the possibility of false and often pathologically mass goal-setting due to the strong dependence of collective dynamics on the state of individuals (e.g., a drunken crowd). As a consequence, the matter concerns not only collective intelligence but also the collective psyche of large systems. The latter term is used in social psychology [71] and underlies *psychohistory* [72]. A combination of collective intelligence and collective psyche at the level of a state and its large social subsystems is usually called an *ideology*.

The confrontation of parties to conflict unites them into a single metasystem, which is also capable of processing and using information. The application of game theory in political science and military sciences is based on the tendency of such systems to equilibrium [73–75]. In particular, the existence of equilibrium configurations even under a strong antagonism of the parties is illustrated by the graph of military losses of the USSR in the Great Patriotic War (Fig. 5). In 1942, the spring offensive of the Red Army in the conditions of the thaw did not achieve its goals and was accompanied by heavy human and equipment losses (with proportional figures for the German army); in the unfavorable periods of spring 1943 and spring 1944, the parties did not conduct intensive combat operations (see the book [76]). Thus, all parties to conflict contribute to the DI of the system of opposing actors. In particular, this fact underlies the game-theoretic interpretation of wars within T. Schelling's *bargaining theory* [73].

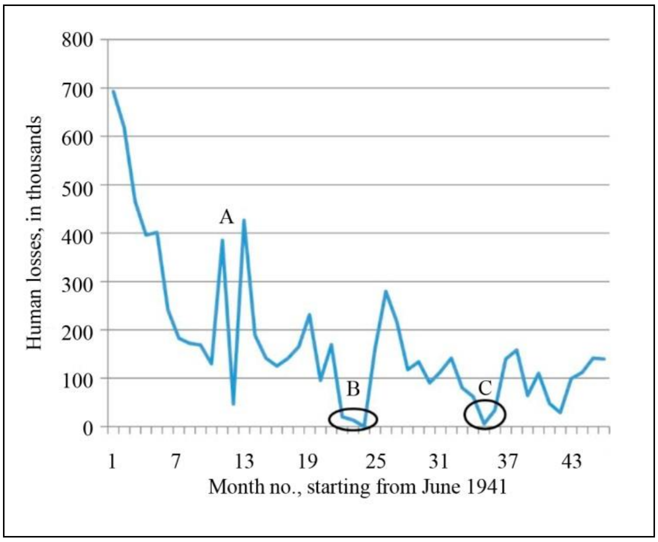

Fig. 5. Monthly military losses of the USSR from June 1941 to May 1945 according to [76]: A—May 1942, B and C—strategic pauses in April–June 1943 and May–June 1944, respectively.

Since the late 20th century, the evolution of mankind as a single system has been discussed in the humanities in the context of the *Universal History* of the Earth, including geophysical, environmental, technical, and social factors [77]. In terms of our survey, this process primarily reflects the dynamics of the DI of world-scale systems (states, peoples, and civilizations [78]) in the historical time scale with its inherent nonuniformity: upsurges, stagnation, and crises. At the universal level, the inseparability of individual human intelligence from the educational and cultural environment is clearly manifested: this fact, trivial for humanitarian knowledge bearers, is still not fully reflected in formal models.

Despite that the DI of the world economic-political system with states as agents is unfortunately not yet able to prevent crises and wars, its activity in peacetime is mainly creative. In this sense, outbreaks of wars and revolutions with the destruction of people, material values, and the least viable social institutions act as analogs of the chaotic movement of agents in the simplest MASS with swarm intelligence. The intermittent improvement of living conditions of the Earth's population, which increased in the 20th century almost fourfold despite wars and epidemics [79], is based on the achievements in technology, economics, medicine, social sphere, and other aspects of implementing DI. At the descriptive level, scientific, technical, and social progress in all known historical periods is obviously the result of developing the collective intelligence of mankind and its large subsystems. This emphasizes the importance of studying DI and ways for its adequate mathematical description.

The representation of society as an "atomized" system of interacting individuals, which emerged in the 19th century, took the emergent manifestations of DI beyond sociological theories, although religious, psychological, and "organicist" concepts of society[5] continued to exist until the first half of the 20th century [80]. In modern literature, the dominating description of an MASS as a set of individual agents with fixed strategy sets does not imply the generation of new features by the system of their dynamic relations. However, the mathematical modeling of historical processes sometimes uses "humanitarian" variables, e.g., the morale of the people (*asabiyyah*, or collective solidarity) in the balance of state resources [81]. This indirectly manifests the objective need to consider the influence of collective intelligence and collective psyche on historical processes.

2. THE FACTORS FORMING DI

All kinds of DI considered in this survey are summarized in Table 1; the efficiency of new information generation is evaluated in the last column on a purely qualitative level. (Question mark indicates the kinds of DI that are not generally accepted.) Even the simplest forms of swarm intelligence, which emerged in different biological species for collective survival, form a flexible response of MASSs to unprogrammed external influences. When treating the adaptive changes of organisms during evolution as the creation of new information, it is necessary to recognize the existence of very effective "evolutionary DI." Despite its use in computational *genetic* algorithms [15], this direction is still poorly developed. The formal description of the DI of the largest-scale social systems—states, nations, and civilizations—is insufficiently studied as well. Nevertheless, global technical and social progress certainly reflects the development of this form of collective intelligence. At the same time, reliable manifestations of the Global Brain, built from users of global computer networks, are not yet known. Given the chaotic structure of networks, the existence of such distributed intelligence is rather a hypothesis.

Let us summarize the brief overview of the known types of distributed intelligence. The modern applications of DI in the field of management, control, and planning are constantly improving, have no clear separation from AI (EI, NIMs), and far excel individual human intelligence by capabilities in some applications when combined with AI. Like the model of a fully rational and omniscient *homo economicus* in neoclassical economic disciplines and game theory, individual human intelligence (HI) is rather an abstraction reflecting the early sociological notions of an "atomized" society [80]. Both of these models implicitly incorporate the influence of collective intelligence (the entire society and the economic aspects of its activities, respectively). The inseparable connection between the HI of individuals and collective intelligence clearly manifests itself at all its levels: learning, personality formation, use of knowledge accumulated by society, creativity, and many others.

Different levels of any carriers of intelligence (people, living organisms, different types of society, technical devices, and systems) are summarized in Fig. 6. The nested features of intelligent agents reflect, among other things, the historical development of their research. At the successive levels of intelligence, its fundamental features (see Section 1 in part I of the survey [7]) can be filled with different content, e.g., from a goal set externally to a robot or ANN, through the disordered but purposeful actions of a swarm, to pursuit of a goal by animals or "intelligent" logistic schemes, and, further, to conscious autonomous goal-setting and its adaptive editing by a creative person.

The outer contour of the diagram in Fig. 6 corresponds to the capabilities of technical devices and automatic control systems, including those not considered intelligent outside of specialized disciplines. The remaining levels are covered by different types of intelligence, including HI or DI combined with AI. Nowadays, the field of artificial intelligence is dominated by third-level systems, which are massive and intensively developed. There are some successes at the fourth level, but the fifth one still remains a dream: the inner shaded area is still the sovereign territory of human intelligence.

[5] Many of these concepts appeared within racial-anthropological theories and ideas of social Darwinism. Therefore, since the middle of the 20th century, they have been forgotten together with the corresponding approaches to analyzing the DI of large systems.

Table 1

The kinds and features of distributed intelligence

Kinds of DI	Intended purpose	Structure	Noise level	Volume of new knowledge
Swarm intelligence (social insects, fish, birds, etc.)	Collective survival	Weak	High	+
The "social" DI of social animals	Survival and collective operation	Hierarchy	Any	++
The crowd wisdom of human communities (mob, market, electorate)	Optimizing collective operation	Weak	High	+
The "evolutionary DI" of biological species	Adaptation and survival of the species	Weak	High	?
Computer simulation of swarm intelligence: agent-based models, NIMs	Reproducing the dynamics of "natural" DI and optimizing calculations	Fixed	Given	?
The AI of artificial social systems (formations of drones, etc.)	Optimizing collective functioning	Assigned	Any	?
The DI of small groups	Decision-making	Weak	Low	++
Hybrid human-computer systems, brainstorming software tools	Decision-making, searching for new information, and collective creativity	Fixed	Given	++++
The DI of organizational systems	Supporting all operation processes of the society	Hierarchy	Low	+++
The emergent intelligence of large-scale systems (transportation, logistics, urban economy, etc.)	Optimizing economic activity and solving given tasks	Complex hierarchy	Medium	++
DI in economics, policy, and military affairs	Optimizing collective operation and solving given tasks	Hierarchy; complex hierarchy	Any	+++
Large systems at the state level and above (history, culture, and civilizations)	Survival; technical and social progress	Complex, weakly ordered	Variable	++++
Hypothetical Global Brain	Optimizing the operation of mankind as a system	Rather unknown	Variable	?

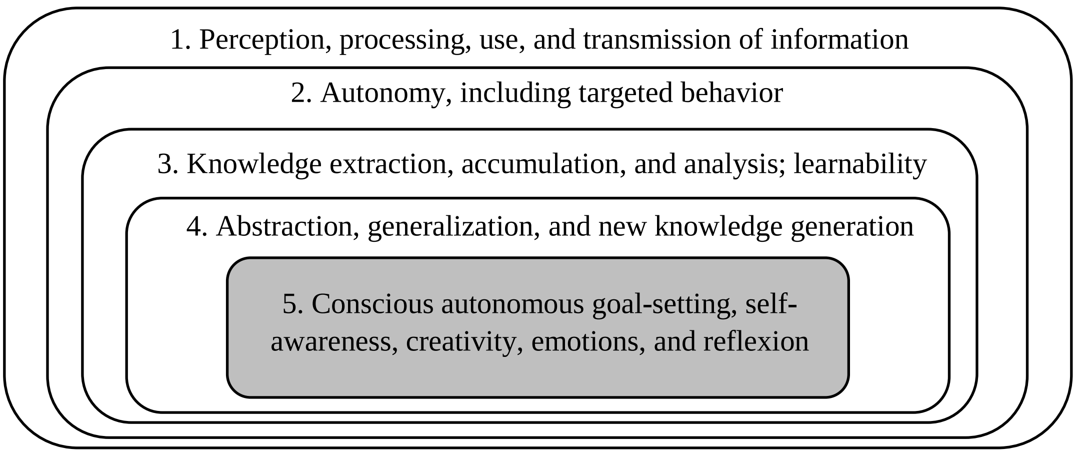

Fig. 6. The general "levels of intelligence" [82, 83].

In the field of DI, intelligent systems sometimes include even second-level systems demonstrating emergent (superadditive) properties as a result of interactions of multiple agents: the expanded field of view of a school of fish, ant paths, crowd wisdom as the averaging of estimates, etc. The third level here includes multi-agent systems for distributed problem-solving (EI, routine actions of OSs) that increase the efficiency of information processing through agent interaction and, moreover, can extract information and learn. Finally, collective human intelligence, as a highly developed form of DI with relatively regulated interactions and partial perturbations of the structure (many organizational systems, including e-expertise, brainstorming, etc.), directly uses human creativity (the fifth level).

A characteristic feature of distributed intelligence in human society is the purposeful strengthening of all features constituting the core of people's intellectual activity (the central block[6] in Fig. 6). At this level, individual and collective intelligences are inseparable (education, organization of creative activity, culture, and civilization) and should be considered in a single context. For these reasons, the classification and formalization of all known kinds of DI remains highly relevant. In the structured subsystems of society, distributed intelligence is implemented as an emergent quality of the "ensemble" of individual intelligences, also with the use of AI in recent decades. Hence, all types of intelligence should be jointly analyzed on the unified background.

Now we list the factors that most obviously correlate with the presence of DI in social systems (including artificial systems) and with its effectiveness. To a greater or lesser extent, these factors manifest themselves in the collective dynamics of all the MASSs considered above; the effectiveness of DI is determined by their combined action. (At the same time, the presence of a leader, planning, reaching consensus, and some other features of the dynamics of human OSs are not as generic and are reducible to particular combinations of key DI components.) In this sense, hopefully, the list below is inexhaustible and sufficiently comprehensive:

1. the multi-agent nature of the system and the presence of connections between autonomous agents;
2. the density and intensity of inter-agent connections;
3. the individualized cognitive capabilities of agents;
4. system structure and ordered agent dynamics;
5. fluctuations in the structure and dynamics of the system and the impact of the environment.
6. information reflection, compression, and recording.

These features are characteristic of any "intelligent" systems, including individual intelligence (as repeatedly noted in the literature on AI and DI in the 20th century, brain neurons act as interconnected elements), ANNs, and NIMs. A fundamental manifestation of multi-agent system's intelligence is "collective rationality," which does not necessarily involve individual understanding of an objective goal. The joint pursuit of a goal not realized by process participants is characteristic of all sufficiently large and complex systems whose objective needs are beyond the comprehension of individual agents, including mass political and social events.

The presence of individual intelligence (the third factor), despite its obviousness for human MASSs, is not a prerequisite: the swarm DI of insects is composed of individuals with low cognitive abilities. In different combinations with the structure and elements of stochastic dynamics, the individual intelligence of agents can be both reduced (a street crowd) and amplified within given tasks (groups of experts, actions of economic agents, etc.).

The fourth and fifth factors, i.e., the ordered structure and its violations, formally contradict each other, but they are implemented together in many "intelligent" systems considered here. (An example is brainstorming schemes and other forms of collective creative activity [38, 43].) Finally, the means of information compression (as a necessary condition for processing an infinite volume of data) and information recording (the sixth factor) are the dynamic "images" of external influence perceived by MASS elements. The imprints of external influences in different systems can be "blocks" of consciousness [84], areas of the cerebral cortex [85], ant paths (see Fig. 8a in part I of the survey [7]), ethical norms in society [56, 57], complex assessments [54], control mechanisms for OSs [47, 48], and many other entities. All these factors determine the mechanism of information processing and effective use in different-type MASSs, i.e., in the varieties of DI considered here.

The rationality of individual behavior of people increases with reducing choice alternatives (crossing the street on a green light and stock market trading with a fixed stock price) and becomes bounded when choosing among many alternatives (trying to cross the street on a red light and stock market trading with high price volatility). The rationality of the collective dynamics of a system also increases when the set of possible actions of agents is limited and when there is a "library" of standard responses to external influences

[6] General concepts, such as *education*, *culture*, *science*, *civilization*, and many others, are actually metaphors for different manifestations of the collective intelligence of large systems.

(a *theater fire*[7]). It can be assumed that all diverse manifestations of intelligence, both individual and distributed, conceal a single mechanism of perception of external influences by an "intelligent" agent based on structuring their features.

The model of "intellectual" information perception and processing proposed in [86] associates with an external influence a finite combination of blocks (modules), each reflecting a certain characteristic (*feature*) of an object. The "imprint" of the influence in the agent's perception is represented by the weighted sum

$$\xi_i = \sum_{j=1}^{n} w_j m_j^{(t)},$$

where $\{m_j^{(i)}\}$ are the modules forming the image ξ_i and $\{w_j \in [0, 1]\}$ are their weights. The combination of several features defines the image of an object like a word in hieroglyphic writing. This scheme serves to represent an unlimited number of external influences in a cost-effective way by small ($n < 10$) combinations of modules under a reasonable library size $N \sim 1000$ (reflecting the technical constraints of human memory). In addition, this scheme reproduces the birth of new information as the construction of a new combination of available modules for an object not encountered previously.

The modular structure of the image of external influences naturally extends to the manifestations of distributed intelligence of multi-agent social systems. In the case of OSs, the function of blocks in the modular interpretation of external influences is performed by service instructions and norms. The role of a "block" image is played by the personnel's actions according to instructions; the correction of the image in changed conditions with the replacement of blocks corresponds to the search for the best combination of available actions; the memorization of new information corresponds to the modification of instructions. In "living" MASSs with more primitive agents, there are modules as well that guide collective dynamics and change in a variable environment: bees dancing in a hive, ant paths, reproducible motion modes of individuals in a flock, etc. (see part I of the survey [7]).

Table 2 illustrates the relationship between the "depth" of the system's collective intelligence and the degree of order of its structure and agents' actions. The strictly ordered operation of the "ideal commission" (the left column of this table) is a heuristic that increases its efficiency. At the same time, a completely informal system without any constraints (the right column) can hardly make any common decision regardless of the intellectual level of its participants. Disordered "human" MASSs or their parts with interactions described by a complete graph are unable to critically perceive external influences and usually serve as an object of manipulation (street crowd [24], information bubbles in social networks [33], the main part of the electorate during an election campaign [22], etc.). At the same time, efficient information processing in ANNs and OSs is directly determined by their rigid structure. Some collective decision processes constituting the core of DI in different-scale "human" systems were analyzed in [87]; the publication [88] presented their identification results for online social networks.

Table 2

Operation features of some model MASSs

"The Ideal Commission"	Political rally	"The Collective Imbecile"
General knowledge of the specialty	General intentions	Nothing in common
Targeted selection of participants by qualification criterion	Random selection of participants based on the proximity of sentiment	Free entry
Strong management (chair with a casting vote)	Weak management	No management
Formalized exchange of information and opinions, excluding emotions	Informal exchange of opinions and emotions	Random exchange of emotions
Quantitative comparison of the significance of opinions (voting)	Declarations of opinions (appeals)	No formulated opinions
Subordination of the minority to the majority	Insubordination of the minority to the majority	No majority
Obligation to execute decisions	No obligation to execute decisions	No decisions

[7] In this classical sociological example, a theater fire threatens to cause panic and stampede despite the high cultural and educational level of the majority of the audience. However, following the orders of their commanders, a company of soldiers in the auditorium is very likely to evacuate everybody without casualties.

CONCLUSIONS

According to the material presented in this survey, the manifestations of DI at all its known levels reveal common features determined by collective processing of information not necessarily reflexed by the consciousness of agents. (In the systems of social insects, fish, and birds, as well as in nature-inspired computational metaheuristics, there is nothing about the consciousness of agents; however, the information content of mass collective processes in human society is usually not realized by their participants.) The capabilities of DI are determined by the intensity and structure of interactions between agents, their cognitive abilities, as well as by the balance between the degree of order of the system and random "noise," which plays an important role in optimizing system dynamics. In several well-known examples (brainstorming, scientific discussion, meetings in a creative environment, etc.), inventing new things is stimulated by the purposeful amplification of "noise," which blurs stereotypes and increases the probability of insight. Analogies in the manifestations of individual, collective, and artificial intelligences—with the necessary reservation about the absence of a generally accepted definition of this phenomenon—indicate the prospect of analyzing all its known forms from a unified standpoint.

The above analysis of different kinds of DI in biological, social, and artificial multi-agent systems shows the similar forms of its implementation and, moreover, reveals the incompleteness of existing formal models, complicating the unified interpretation of this phenomenon. Given the abundance of publications and directions in the field of cognitive sciences, the aspects of intelligence under consideration still contain no formal algorithms for inventing new things, i.e., creating previously non-existing knowledge beyond its logical inference. While classifying the stages of creative activity [83], modern models face the necessity to create mathematical images of objects that do not exist within the available set of knowledge before executing some creative act; modern mathematics, apparently, does not yet possess a developed apparatus for describing the nonexistent. At the same time, the modular model of perception circumvents this problem by presenting new images as a new combination of the features of external influences already known to the agent.

All aspects of intelligence activity are reproduced to varying degrees in the cooperative dynamics of diverse multi-agent systems, indicating the presence of DI in such systems. The numerous forms of DI in biological and human communities overviewed here demonstrate both the obvious parallels of DI dynamics with the manifestations of individual intelligence and the absence of emergent effects of the birth of new information in its existing theories. Meanwhile, such effects are reproduced by phenomenological multi-agent models, are used in modern natural computing algorithms, and are directly considered in DSSs and other computerized tools for supporting human intellectual activity. The unified formal modeling of both individual and distributed intelligence therefore seems to be a very topical problem.

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