Reasoning and learning in a digital economy. Technological challenges of the modern age

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Abstract. Rapid growth in the digital economy creates both additional opportunities and additional challenges for organizations. Artificial intelligence and robotics facilitate and automate a large number of human tasks. Today’s tools — “intelligent assistants” — in large part are capable of processing incoming information, which in the past was processed exclusively by humans. These changes will lead to a significant change in the labor market. Leaders in the new knowledge economy will differ not only in being aided by “intelligent assistants”, but also in how their employees interact with these tools and make complex decisions required for their work. The greater is the use of “intelligent assistants”, the more important will be the decisions that people will make between each other. Organization of continuous training of employees in effective communication is today an increasingly popular innovative strategy in companies. How do we remove communication barriers between employees, between teams, and between man and machine? This paper proposes a solution to the posed problem of ensuring the most effective communication using methods developed in physics of the mind and Dynamic Logic.

1. Problem statement

According to Moore's law the number of transistors in an integrated circuit chip doubles every 24 months, while according to the forecast of David House of Intel — every 18 months. The speed of computers is growing even faster. Such rapid change makes a lone person powerless and obliges him to effective cooperation, which is not natural to humans; it requires personal effort and constant practice. Artificial intelligence and robotics facilitate and automate a large number of tasks. Today’s tools in the form of “intelligent assistants” are more capable of processing incoming information, which in the past was processed exclusively by humans [1, 2]. Leaders in the new economy will differ not only in being aided by “intelligent assistants”, but also in how their employees interact with these tools and how they make complex decisions required for their work [3, 4]. The greater is the use of “intelligent assistants”, the more important will be the decisions made by humans. This in turn increases the importance of continuous training of employees who need to keep up with machines and be able to interpret their results [1, 5–7]. In addition, we live in a world where companies must quickly adapt their strategies in response to global competition and to structural changes in industries caused by the digitalization of products and technologies. This means that the gap between the development and execution of a company’s strategy will only increase, and organizations have to constantly adapt, to learn during the strategy implementation process. The beneficiaries will be those companies that are able to faster obtain
new knowledge in minimal time and with minimal costs [8–10]. The speed of learning is the result of experimenting and interacting “all-with-all” without barriers both inside and outside the organization. Intelligent assistants are ready to process huge amounts of information in little time. But how do we make them understand the language we use to ask them questions? Anyone who has searched for information on the Internet is familiar with the frustration brought on by these searches: Google, Yandex and other search engines do not “understand” language, they search for information based on word matches and deliver millions of gigabytes of data that you do not need. But in the continuous process of updating technology new programs are already being created that use the latest results of the mathematical theory of intelligence that connects language and thought. Brain structures for learning concepts are called models of our mind. They model the world around them, and the result of this simulation is “phenomena” perceived and cognizable by thought. What do models consist of and what do they look like? What is their mathematical nature? In Neural Modeling Field Theory (MFT) the initial brain structure models are vague, like looking through frosted glass, and do not look like photographic images of objects. They are described by fuzzy logic, solutions of which are continuous and different from simple binary “yes/no”. In the process of learning, models “take shape and properties” of specific objects, while maintaining some fuzziness so that in the process of perception they can adapt and “take the shape” of a particular object in its aspect, lighting, and movement. The same process occurs in communication between strangers and teams who differ in their “language” of communication. How do we remove communication barriers between teams and between man and machine? How does the nature of emotions manifest itself in learning? We will consider the solution to this problem of communication in terms of physics of the mind and Dynamic Logic [11].

2. Problem solution

The term “teaming” in the sense of “interaction in a dynamic team” was first described by Amy C. Edmondson in 2012 [5, 6]. This way of interaction is very flexible and allows easily combining interpersonal communication and competition, achieving set goals and ensuring psychological safety for all team members. Today leading companies use teaming to make deliberate meaningful changes in behavior and to solve management problems in the context of accelerating changes, turning it into a competitive advantage [4]. This is exactly what allows us to define teaming as a breakthrough technology. McKinsey’s research suggests that the gap between industry leaders and laggards is explained in the paradigm of companies adopting analytics only within the industry vs. cross-industry analytics, and this gap is growing [12]. Experts have even introduced the concept of data culture, explaining the need for the formation of certain work principles with the increasing data influx [13, 14]. At the same time a number of researchers note that the competitive advantage of modern algorithms and robotics will soon decrease, while the supply of new tools (intelligent assistants) that use big data in the process of making important decisions will increase [15]. Meanwhile the complexity of coworkers’ decisions will increase as well. This increases the importance of the employee’s interpretation of results offered by the intelligent assistant, and as a consequence increases the importance of training decision makers who must be able to interpret the results of big data processing. Two important trends can be noted: the first is the structural changes in companies caused by the digitalization of processes and objects, and as a consequence — the emergence of new competencies caused by cutting-edge analytics; and the second is that the learning process has moved from classrooms to workspaces. The employee is now learning in the process of completing a task. This significantly changes the learning paradigm. If the student feels comfortable in the classroom, understanding that he is solving test problems, then the employee must train in the process of making responsible decisions. The learning process necessarily involves the right to make mistakes. But how do we accept this in the process of execution of duties? Both managers and employees ask themselves this question. How do we draw the line between where the error is permissible and where it is not? Answers to these questions were attempted to be found by those who were the first to explore previously unexplored domains: jungle, sky, space, nuclear energy, etc. They all considered an error to be a hint. But, aside from that, an important aspect is the attitude of others to the proposed methods. Cooperation, empathy, openness, and trust are components of utmost
importance to the learning process happening in the workplace. The ability to accept that which does not fit within our vision's boundaries is a critical factor in development. Artificial intelligence must be defined within the boundaries of what it can and cannot do. Big data allows you to quickly identify possible paths, but it is a human who must manage the consequences of decision-making. This shows the gap between knowledge and meaning, the latter of which is determined by rules. New knowledge comes out above the rules. What criteria should guide people in making decisions? This is a question that today many researchers are looking for an answer to.

3. Results
What principles govern an employee's decision-making with the aid of an intelligent assistant? How do we determine the conscious and unconscious in decision-making? We try to apply modern theories of mind modeling and artificial intelligence to describe the mechanism of learning and decision-making done in the midst of the technological challenges of our time that emerge in the digital economy. We accept the theses of physics of the mind, first developed by Perlovsky [11, 16], as the basis of the principles of mathematical modeling of psychological mechanisms at the functional level. Perlovsky was first to suggest that people have a knowledge instinct (KI), seeking to reduce cognitive dissonance. This assumption was confirmed experimentally [17]. Perception and cognition lie in the adaptation of internal models (model-concepts and models of behavior) to the surrounding world. The knowledge instinct is an instinctive mechanism associated with knowledge acquisition and the improvement of concepts. The fundamental nature of this mechanism is that our knowledge must always be changed to fit current scenarios. Knowledge is not just a static state — it is in a constant process of adaptation and learning. Without the adaptation of conceptual models we would not be able to understand the ever-changing world around us. We would not be able to navigate or satisfy any physical instincts. Hence, we have an innate need — an instinct — to improve our knowledge. This mathematical principle and dynamic law that manages processes is targeted towards the satisfaction of the learning instinct. In other words, the learning instinct or knowledge instinct is the basis of the mechanism that "drives" the processes of adaptation of internal models, and an integral part of this mechanism is an aesthetic emotion that measures and signals the degree of satisfaction or dissatisfaction of the learning instinct. Bar and his staff at a lab for brain studies at Harvard showed that vague representations are less accessible to consciousness than are clear visual perceptions [18]. This leads to unexpected conclusions about the mind's hierarchy. Abstract representations at high levels in the hierarchy are not based on direct clear perception, but on many levels of vague representations and concepts in language. The “higher” in the hierarchy, the vaguer and less accessible to the consciousness are the mind's representations, the conceptual content of which is mixed with their emotional content. Simple objects are perceived at the lower levels. Further up is the understanding of general and abstract concepts that unite the knowledge of the lower levels. At the top of the hierarchy are concepts that unite all our knowledge, the concept of the meaning of life and the purpose of existence. Mathematically, the knowledge instinct is described as the process of maximizing similarity between higher-level and lower-level models. The cognitive hierarchy is an approximately hierarchical structure that extends from sensory perception to abstract cognition [19, 20]. Aesthetic emotions measure satisfaction or dissatisfaction of the knowledge instinct. Mathematically, this can be represented as the rate of change of the similarity function. This has been experimentally confirmed [17]. Various attempts of artificial intelligence algorithm developers at building their models on the comparison of sensory images with a set of models stored in memory led to failures associated with the complexity of calculations. Dynamic Logic (DL), which Perlovsky was also first to propose as a mathematical apparatus, makes it possible to compare vague models with clear images coming from the retina [21], overcoming the complexity of calculation. It allows you to model the process from uncertain to clear states and avoid logical states until the very end of the process. Bar demonstrated this experimentally [18]. Thus, each higher-level concept and its corresponding mechanisms in each person develop individually, through evolution, with the aim of turning several lower-level concepts into a single knowledge at a higher level. This allows a person to develop more broadly, to form a more abstract understanding of the outside world. Models at the top of the hierarchy
form the whole life experience of a person, his values. The working of the mind can be formulated as a struggle between the knowledge instinct and ready-made rules. Rules give confidence based on thousands of years of cultural experience, though may not quite match your individual situation. Knowledge instinct is accompanied by doubts and uncertainty but can lead to higher satisfaction. In any research study with team interaction a situation arises where one must make a choice between independent thinking and ready-made rules. But making this choice is always the hardest work. Mathematically, it is possible to formulate the utility function so that the knowledge instinct and the rules converge. Such a “utility” measure will take into account the importance of quick decision-making for survival, as well as the limitations of any personal experience, uncertainty in observations and data, and the need to limit the possibility of worst-case outcomes versus maximizing “benefit on average”. The utility function can even take into account the fact that the future is unknown, so personal experience must be combined with the knowledge accumulated in culture. When a person obtains a result in the process of learning, he experiences strong aesthetic emotions. Often this is manifested at the physiological level, e.g. aesthetic chills [17, 22]. The same happens in a team — when a group shares a common goal, when each member of the group focuses on it. An example is the reaction of a stadium to the victory of a team, or the joint singing of the anthem. This state can be described by the term “synchronicity”. The same state occurs in groups undergoing training in teaming, when participants, for the first time having set themselves a “super-goal”, begin to jointly show empathy, proactivity, the ability to hear and listen, removing the status hierarchy and distance. Obtaining knowledge about others' plans and intentions becomes a significant aspect of the knowledge instinct. Without this intention for your own consciousness the success of work done in the team will be minimal. In a situation where each team member interacts with his intellectual assistant that gives him a large number of different solutions, understanding the goals and objectives of other team members, often interdisciplinary, becomes a major advantage. Such examples of interdisciplinary collaboration are evident in R&D teams in the development of new products and technologies. For the development of a new product the cascading of goals from top to bottom is seen as a primary process of team organization, as a language of interaction between team members, and as a formation of mutually exclusive requirements (dissonances), and the team's implementation of the project transpires from the bottom up as a process of obtaining knowledge, through removing dissonance. This explains the emotional reaction of a researcher to solving even the smallest problem. Aesthetic emotions correspond to the satisfaction of the knowledge instinct. A study of 224 corporate R&D groups found that the exchange of views between people with a wide range of knowledge was the key to maximizing team performance [23]. It may be assumed that the models in the hands of researchers are always cognitive. Mathematically, this can be formulated as a change in the probability that sensory signals correspond to their cognitive models. If the function reaches a local maximum, the rate of change approaches zero. Depending on the sign of change, emotions can be both positive and negative. The key factors in the formation of cognitive models are life experience and language [24, 25]. Language and cognition are organized in an approximate dual hierarchy [11]. The dual hierarchy model specifies that each representation consists of two parts: cognitive and linguistic. Cognitive models combine language with experience. The language of communication determines which lower-level concepts make sense to learn as higher-level concepts. Language defines bits. Language representations exist in the world around us and are studied at an early age. Cognitive representations are studied in the process of experience under the guidance of existing language representations. The diversity of knowledge in interdisciplinary teams expands the range of perspectives that can be used for innovation. However, when organizations gather groups of people with different knowledge to develop a new product or service, or to solve a complex problem, the problems of team interaction become especially significant [26]. These problems can be divided into three types: division (opinions, convictions, values and relations), variety (content expertise, functional background, network connections and industry experience) and inconsistency (payment, income, prestige, status and power) [27]. A variety of knowledge, in itself, does not give an advantage in efficiency. The interaction of team members, whereby a variety of knowledge will be used, becomes a key factor. In most studies team effectiveness was determined by the model proposed by McGrath [28]. The model he developed defines
the dynamics of team performance, characterizing the interaction between a) emerging affective, cognitive or motivational states, such as relationships, values, cognition and motivation of team members; and b) team processes in which team members interact with other members and their work environment in the form of cognitive, verbal and behavioral actions. A further development to this model was the model of cross-boundary interaction [7]. This model, based on a variety of knowledge, expands the range of views and ideas that teams can use for innovation. The model assumes three boundaries of knowledge, which vary in thickness: syntactic, semantic, pragmatic. According to the model of cross-boundary interaction, the initial states of a team's knowledge are formed with the help of knowledge attributes of its members, who participate in cross-boundary interactions. All this knowledge affects each other. The resulting mutual influences create feedback that transforms and upgrades original knowledge, generating evolution in the team's communication language, in the interpretation of the results of its work, and in the evaluation thereof. Such iterations will continue until a result that suits everyone is achieved. The iterative process goes, gradually clarifying, from the coordination of general (vague) principles to that of communication details. The problems of interpersonal, cross-boundary communications, as well as the problems of obtaining knowledge and learning, are difficult to formalize. Therefore, it is advisable to develop cognitive algorithms using the proposed mathematical apparatus of Dynamic Logic, guided by the knowledge and concepts that characterize communication.

4. Conclusions. Vectors for future research
The development of modern mathematical methods, such as Dynamic Logic, permitting not to have to calculate all possible combinations but use the “vague-to-crisp” principle, allows building cognitive models of learning based on hierarchies. The development of methods of organizational learning concentrated in teaming allows forming a complex hierarchical system of relations in teams based on the principles of “from primary to secondary”. Complementary research of these methods and construction of mathematical models of mental hierarchies of team interaction will allow developing algorithms necessary both for the creation of intelligent assistants and for the creation of human-machine interfaces.

The considered mathematical models and mechanisms of effective communication and knowledge acquisition can be used in companies both in engineering applications of artificial intelligence and in the practice of organizing team interaction. Cognitive algorithms try to combine the mental abilities of a person with the enormous computational power of a computer. It is in demand in the intelligent assistants being developed, in fast calculations and in big data.

Two areas of future research are particularly important for understanding team collaboration issues: team performance research and studying the increment of knowledge in organizations. The first stream focuses on the group dynamics and measures team contribution, processes and emerging states and results, while the second carefully explores the models of mental hierarchies. Undoubtedly, it will be interesting to learn how to measure the “ability to learn”.

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