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SOLVING SMALE'S 18TH PROBLEM

Abstract: *Having analyzed the history of scientific discoveries and data provided by cognitive psychology, neurophysiology and the theory of artificial intelligence, the author has come to the conclusion that the main factors excluding the algorithmic character of creative activity in science are as follows: the stochastic nature of inductive inference, the trial and error method (brute force method), the factor of chance in scientific discovery and Gödel's incompleteness theorem. This allows solving Smale's 18th problem: What are the limits of intelligence both artificial and human?*

Key words: *creative activity, artificial intelligence, inductive inference, the factor of chance in scientific discovery, Gödel's incompleteness theorem.*

Аннотация: *На основе анализа истории научных открытий, а также данных когнитивной психологии и теории искусственного интеллекта установлено, что основными факторами, исключающими алгоритмический характер творческой деятельности в науке, являются вероятностная природа индуктивного вывода, метод проб и ошибок (метод последовательного перебора), фактор случая в научном открытии и теорема Геделя о неполноте. Это позволяет решить 18-ю проблему С. Смейла: каковы пределы интеллекта, как искусственного, так и человека?*

Ключевые слова: *творческая деятельность, искусственный интеллект, индуктивный вывод, фактор случая в научном открытии, теорема Геделя о неполноте.*

1. Introduction

In 1997 S. Smale, an outstanding American mathematician, defined eighteen unsolved problems in mathematics. It is needless to say that these problems are notable for their high degree of complexity. Suffice it to recall Poincaré conjecture (the second problem proposed by S. Smale) about the equivalence of topological properties of simply connected three-dimensional space and the 3-D sphere which had been unsolvable for 100 years and proved by G. Perelman in 2002.

In the list of S. Smale's problems the 18^{th} position is occupied by a problem related to the limits of artificial and human intelligence. In his lecture "Mathematical Problems for the Next Century" [1] delivered at Vladimir Arnold's 60^{th} Anniversary Conference which was held at the Fields Institute in June 1997 (Toronto, Canada), S. Smale asked mathematicians a question: "What are the limits of intelligence, both artificial and human?" Further on, S. Smale elucidated his point: "Penrose in [42] attempts to show some limitations of artificial intelligence. Involved in his argumentation is the interesting question, "is the Mandelbrot set decidable?" (see problem 14) and implications of Gödel's incompleteness theorem. However a broader study is called for, one which involves deeper models of the brain, and of the computer, in a search of what artificial and human intelligence have in common, and how they differ". He also added that he would start research in the area where along with the theory of real numbers, approximations, the theory of probability and geography a considerable role is played by learning, problem solving and games theory [1, p.297]. Referring to R. Penrose [42], S. Smale had in view his monograph "The Emperor's New Mind" (1989).

2. Topical issues of artificial intelligence

2.1. Sensory perception

A human being experiences the world outside through his senses. Sensory perception is the initial segment in the chain of events related to information (input signals) collection and processing. It is based on an individual's sensory system comprised of five types of sensitivity: vision, hearing, olfaction, somatic sensation, and taste. Accordingly, perception is initiated by external signals (stimuli) consisting of light, sound, molecular compounds and pressure. These stimuli detected by the sensory organs are converted into statements comprehended by the brain. Events are perceived and immediately interpreted (represented) by neural ensembles. Interpretation is based on existing knowledge which, in its turn, is corrected and supplemented by new sensory signals. Expectations (preliminary assumptions) that we have regarding what we can see or hear directly influence our perception which enables to remove ambiguities in sensory information interpretation. On the other hand, sensory signals occasionally alter our expectations, set classification and categorization frames for external objects. Here, feedback loops are abundant – information flows up and down a complex branched hierarchy. The human brain is veined with feedback links. For instance, exchange between a new cortex (neocortex) and all other brain parts including thalamus (main subcortical sensory center) takes place in such a manner that the amount of feedbacks exceeds that of outputs by almost ten times! According to J. Hawkins, "that is for every fiber feeding information forward into the neocortex, there are ten fibers feeding information back toward the senses" [2, p.33]. Thus, the feedback principle providing for interaction between various sensory structures and information storage and processing centers should become one of the major principles for functioning of the artificial intelligence.

Another important peculiarity of perception and processing of inputs in the human brain is the principle of invariable structure formation. When we see, sense or hear, the cortex receives impressions which it preserves in an invariant form. The ability to invariant recognition appears in living organisms at relatively early ontogeny stages. During training the visual array constructs 3D models of objects in an observer's mind based on 2D projections of presented objects. These 3D models are remembered as templates. Further on, these templates based on highlighting the key properties of objects and neglecting minor ones are used for identifying new images. Notwithstanding the fact that depending on the observation angle, size and illumination of an object, the eye retina receives numerous differing 2D representations, the brain identifies invariant properties of the object and successfully recognizes it. For present-day computers this task is either very complicated or impossible at all. A computer is not able to make a decision about the relation of presented projections to this or that object, i.e. it is not able to recognize an image if it has been moved, rotated or its size has been changed or it has been transformed in some other way.

Therefore, it is vital to develop such artificial intelligence systems that would possess the ability to form invariant (abstract) structures when numerous and constantly changing input signals are perceived.

2.2. Memory

Memory capacity of modern computers is constantly growing; however, the structure of their memory is fundamentally different from the way the human brain stores and retrieves information. J. Hawkins [2] describes main features of our memory:

- the neocortex stores sequences of patterns instead of single patterns of the visual environment;

- the neocortex recalls patterns auto-associatively;

- the neocortex stores patterns in an invariant form;

- the neocortex stores sequences in a hierarchy.

An example of a sequence of patterns is our memory of the alphabet. We all know the alphabet, but if we try to say it backwards, we easily understand that it is not an easy task at all. Our memory stores the alphabet as a sequence of patterns. This is the reason why it can’t be instantly or randomly retrieved. Our memory of songs is another example of temporal sequences. Knowing a song doesn’t allow recalling the words backwards or spreading our attention over the whole song. We recall it only in the order we learnt it. The same holds true for a lot of other information. Contrary to our brain, computer memory doesn’t store sequences of patterns. As J. Hawkins notes, various software adaptations can help to achieve it but computer memory is anyway unable to fulfill this task automatically.

Our memory is of auto-associative nature. Neurons specializing in imprinting inputs constantly associate them with one another. Comparison (correlation) of various information units and fragments determines our ability to notice similarity between them, which eventually enables to draw analogy between facts and ideas. When the brain is solving complex tasks, it retrieves knowledge from memory by association. This knowledge has been used before in solving similar tasks and the brain uses it in a new situation. Even words are stored in the neocortex in a bound (associated) state. This is well known to psycholinguists who have introduced the notion of logogen. Logogen is a unit of a word recognition model (a memory block that like a “hub” connects all aspects of a word). T.N. Ushakova in [3] notes: “The aggregate of numerous interword links forms the so-called verbal network (web). The verbal network is a psychophysiological formation developed in childhood (and in any age if studying foreign languages) and then sustained in the brain during its lifetime. All words known to a person are incorporated into its structure in the form of logogens. Connected by numerous “interlogogenic”, interword links, logogens become constituent elements, verbal network hubs” [3, p.207]. When we spot the logogen of a name (word), the relevant field in the verbal network is activated. Words and verbal clichés related to the recognized word turn into an active state. Based on diffuse activation, relevant specific word logogens are spotted. Owing to auto-associative nature of our memory we are capable of recognizing (recalling) an object by one character and the set of features by this object. In other words, our brain is able to compliment images, retrieve a full picture based on incomplete or distorted input information.

Modern computers are not capable of that. For several decades, scientists have been trying to create auto-associative memories in artificial neural networks; however, the obtained results are not very impressive. Computers search the memory for information consecutively instead of associatively, which takes a huge amount of time. As G. Luger notes in [4] people are much faster in solving tasks when they get more information while computers, on the contrary, slow down their work. This delayed action takes place due to the increase of time spent on consecutive search in the knowledge database [4, p.52].

One of the ways to increase the efficiency of computer memory may be the use of so-called chaotic algorithms. Some researchers pin high expectations on such algorithms, they particularly hope to provide artificial intelligence with the ability to search for information associatively. A. Dmitriev in [5] writes: “Users’ golden dream is, instead of searching for music, video or photos by their attributes (directory and file names, date of creation, etc.), to search by content or association, so that, for example, a piece of music would be found by a fragment of a tune. It appears that such associative search can be performed using technologies based on deterministic chaos” [5, p.50].

The fourth principle according to which our memory functions and which distinguishes the brain from computers is the hierarchic storage of information. Any hierarchic system is characterized by the position of its components – some are located above the others. All functional areas of the brain “dwell” in the same cortical tissue. However, one area is “above” or “below” the other depending on their relation and interaction. Primary sensory areas of the brain directly receiving the information about the surrounding world are lower functional areas. They process primary information on the simplest, basic level. For example, visual information passes to the cortex through the primary visual area (area V1). Area V1 is responsible for perception of minor contour segments, simple motions, basic colors, contrast signals. Area V1 sends information to other areas called secondary areas (V2 areas) forming unified images out of individual components. In their turn, having processed the signals, secondary areas pass them to associative areas where comparison (association) of different unified images takes place.

A similar hierarchic structure is found in other brain divisions, as well (auditory, tactile, motive, etc.). Information signals in the cortex are passed in two directions: from lower-order areas to higher-order ones and backwards, in a top-down direction, with downward reverse information flows having large information richness.

The immediate task faced by computer science is to develop artificial neural networks (ANN) possessing hierarchic memory organization. Unquestionably, this will be a step on the way to the development of self-learning computers. Indeed, self-learning presupposes consecutive ascension from specific (detailed, fragmentary) knowledge to abstract (generalized, integral) representations.

2.3. Speech understanding

Modern speech recognition software programs function successfully in a very limited amount of cases when the number of words that a person can utter is strongly limited. However, a person recognizes speech effortlessly because the neocortex both perceives single words and anticipates the content of entire sentences, as well as the framework of the general context. In the course of oral speech recognition, we foresee ideas, phrases, and single words. Moreover, the cortex does it automatically. The necessity to forecast is related to the fact that verbal statements exchanged by people depend on the context and a range of other things preventing the unambiguous interpretation of speech. Many modern psycholinguists underline the variability of a speech signal and its essential imperfection. As a result, a listener does not retrieve information from an acoustic speech signal but rather remodels the statement building upon some acoustic features and using heuristic procedures based on ultimately broad grounds ranging from the interlocutor’s knowledge to the overall picture of the world. Some cases of speech perception and understanding include the stage of probabilistic identification of words within the framework of similarly probabilistically identified syntax structures. In human speech, things untold are as important for effective statement as those uttered. To apprehend the latent content, different types of discourse should be used.

The impossibility for a computer to interpret speech correctly is attributed to the fact that it functions as it was programmed and doesn't learn from its experience. Through learning, a child masters the vocabulary in which every word denotes an object, action or the description of an object. In their turn, adults constantly influence this learning process encouraging proper speech actions a child makes and correcting mistakes. Perceiving a situation (an object or action), the child's brain links (associates) the situation with the word. Multiple repetition of these interconnected events leads to formation of stereotypes, i.e. apprehension of any given words stored in memory. Generalizations can occur here. They follow the scheme: this word was uttered simultaneously with the presentation of a specific object or action; subsequently, this word is linked with this or that object or action. Such generalizations enable to develop a generalized association (abstract stereotype) which is an important component of the ontogenesis of speech acts. Eventually, they enable to develop a generalized association (abstract stereotype): every single thing or action has a name. Mastering words (nouns, adjectives and verbs) and first grammar rules taken over by imitations enables to make up simple phrases at first and then complex sentences.

To apprehend speech, i.e. the meaning of sentences revealing the essence of different situations, a computer should, in the first instance, have experience in facing such situations. For this reason, J. Hawkins notes that to understand human speech to a full degree, a machine should "experience" much and "learn" the same things as people do. Perhaps, it will take many years to create an intelligent machine that understands language the way people do [2, p.213]. The same is mentioned by S. Russel and P. Norvig in [6]. The say that a translation task is very complex because deep understanding of the text is needed to solve it, and this, in its turn, requires deep understanding of the situation in question. This affirmation is true even for very simple texts, in particular, for "texts" consisting of one word [6, p.1025]. Summing it up, artificial intelligence capable of understanding a natural language, at least, requires semantic and syntax rules, knowledge about the world and social context, and some methods for processing ambiguities present in a conventional language.

2.4. Performing complicated motor actions

A human being wouldn't have been able to acquire knowledge if he or she hadn't possessed a body. To receive information about the structure of surrounding objects, they have to be physically influenced, with the forms of influence being so plentiful that it is impossible to enumerate them. One of the factors that predetermined the development of knowledge in a human being was the production of tools. A hand freed from the function of walking was needed to perform tens of various motor actions related to the production of tools. With the advent of experimental science that gave a powerful impetus to the development of the society, the role of a human hand increased manifold. Indeed, any experiment can be performed only in relation to "hand" production of various devices and technical means enabling to penetrate the secrets of nature.

A bright example for this is the performance of experiments that enable to study unusual electronic properties of graphene. For this research, Konstantin Novoselov and Andre Geim received the 2010 Nobel Prize in Physics. In his Nobel lecture, A. Geim [7] wrote what incredible craftsmanship of fingers was required to prepare graphite crystals for studying their electronic properties: "To transfer the crystal (~ 20 nm thick) by tweezers from the tape and then make four such closely spaced contacts by using just a toothpick and silver paint is the highest level of experimental skill. These days, not many researchers have fingers green enough to make such samples" [7, p.1290].

Hand work in question has to become the property of artificial intelligence for it to approach the perfection of the human mind (mind without a hand is a helpless child). At present, machines (robots) do not possess the fine and refined movements typical of a human hand. When specialists try to program the movement of a robot arm for it to be able to catch a ball, they have to solve complex mathematical equations. First, they try to calculate the trajectory of the ball and identify its spatial layout in the moment when it contacts the arm. Then they perform calculations determining all crooks of the robot's elbow, i.e. the locations of its hand at different moments. But, the human brain solves the task of catching a ball in a different manner. It simply addresses the memory storing motor impulses for catching a ball. These motor commands appear in the memory after a person through trial and error has learnt to catch a ball. The brain doesn't solve any complicated equations, it simply automatically activates memories of the sequence of movements necessary for catching this or that object.

J. Hawkins in [2] describes this situation as follows: "The memory of how to catch a ball was not programmed into your brain; it was learned over years of repetitive practice, and it is stored, not calculated, in your neurons" [2, p.72].

The memory of motor commands typical of the human brain complies with the same principles as the memory of visual, auditory and tactile signals: 1) memorization of a sequence of patterns, 2) auto-associative retrieval of the sequence of patterns, 3) memorization of the sequence of patterns in an invariant form, 4) hierarchical organization of memory. As is the case with the formation of memory traces of visual and auditory signals, feedback plays a fundamental role in the formation of information about motor commands in the brain.

Thus, artificial intelligence should possess the ability to perform complex motor acts. And, for this purpose it will have to be endowed with a storage system for information about motor commands in accordance with the principles of associative, hierarchic and invariant coding of this information.

2.5. Connectivity problem

Due to the fact that sensory perception, speech understanding, performance of complex motor acts, and the implementation of other functions are impossible without the hierarchical memory system, the main task in creating a sensible machine is to create such a system for storing and retrieving information. In its turn, the main difficulty in creating the specified memory system will be the solution of the connectivity problem, similar to the connectivity of a billion nerve cells (neurons) of a living brain. The thing is that our unique ability to memorize, store and retrieve this or that information, according to the principle of association, is determined by the coordinated work of tens of billions of nerve cells (neurons), with each of them being associated with 5 or 10 thousand other such cells.

J. Hawkins notes: “This type of large-scale parallel connection cannot be implemented on the basis of traditional techniques for producing silicon chips. The latter is created by applying several layers of metal, each of which is separated from the subsequent insulating substance. (This layering process has nothing to do with the layers of the cerebral cortex). Layers of metal contain the "wires" of the chip. Within one layer, the "wires" do not intersect. Therefore, the total number of wired connections in the chip is limited. On the basis of such connectivity, it is absolutely impossible to create a brain-like memory system for which millions of such connections are really needed. Silicon chips and white matter are not very compatible with each other” [2, p.205].

Thus, full-fledged self-learning processes will become available to the computer when it acquires a powerful auto-associative memory system, and to create such a memory it’s necessary to solve the technical connectivity problem. As soon as ways to solving it are found, computers will approach the capabilities of human intelligence.

3. Analysis of factors excluding the possibility of algorithmization of creativity in the field of science

3.1. Stochastic nature of inductive inference

Notwithstanding the fact that researchers developed numerous strategies, techniques and rules enabling to solve the most complex scientific tasks, generate new ideas and even make discoveries in the field of science and technology, human creativity is determined by factors excluding the possibility of rigorous algorithmic description of this activity. These factors don’t leave any chance to hope for an algorithm (a system of instructions) to be once developed and always ensure a correct solution.

We encounter the first factor while analyzing logic means (logic procedures) used by a human being in scientific work. Needless to say, the question is not about deduction. Indeed, deductive reasoning allows formalization, i.e. development of an effective algorithm turning a certain type of reasoning into a computation process. If an algorithm (the sequence of actions sustainably leading to a solution) is known, it can always be used as a basis for a software application. In this case the question is about inductive processing of information. At the same time by induction we mean both the traditional ascent from single facts to general conclusions and the movement from the particular to the particular (analogy). In the majority of cases, scientists use incomplete induction in which conclusion doesn't necessarily follow from the premises and may lead to error. Several reasons can be indicated why incomplete induction finds wider use in scientific activities (i.e. why complete induction is often unachievable). Firstly, components (constituent parts) of many aggregates are so numerous that a scientist is often short of life time to sort out and analyze the components. If an aggregate is infinite (i.e. its components are uncountable), the analysis of these components required for the complete induction becomes an unattainable goal. Secondly, objects of an aggregate become unavailable and material resources that can make them available for research become limited. Due to limited resources, we can't use complete induction again and therefore are satisfied with the incomplete one. Thirdly, objects can be unavailable for research as science has not yet reached the required level of development, i.e. the perfection level of experimental equipment that can be used to study these objects. The high frequency of incomplete induction failing to cover all components of the aggregate on which a generalization is made determines the correctness of statements by many authors (Gottfried Leibniz, Bertrand Russel, George Polya, etc.) regarding the fact that induction doesn't provide the truth but its probability. The same factor determines the correctness of categorizing induction and analogy to plausible reasoning.

As long as inductive thinking strategies instead of the truth ensure its probability, attempts have been made to apply the mathematical theory of probability (statistics) to induction. However, these attempts failed because before any aggregation is studied its structure (number of its typical components) is unknown and when the study is complete (when the structure of the aggregation becomes studied) the post-evaluation of the plausibility degree of inductive conclusions loses its value. Touching upon this matter, B. Russel in [8] writes that since Laplace’s times many attempts had been made to demonstrate that the probable plausibility of the method of induction results from the mathematical theory of probability; but now everybody admits that these efforts were unsuccessful [8, p.352]. He continues explaining that the mathematical theory of probability doesn’t provide anything that would justify our understanding of both general and particular induction as probable no matter how many favorable cases are identified [8, p.361]. The same is mentioned by G. Polya in [9]. He says that no one has yet proposed a clear and convincing method for calculating plausibility in non-trivial situations, and if we imagine specific situations when correct evaluation of plausibility is needed, we can easily understand that any attribution of certain numerical values to plausibility can easily make one look silly [9, p.368].

The possibility to make an error (arrive at wrong conclusions) when using induction and analogy deprives us of the potential formalization of these types of inference in the way it can be done with regard to deduction. For inductive inference it is impossible to develop an effective algorithm, a computational process sustainably producing valid results. Thus, a software application performing induction will produce relevant information (consistent with reality) in some cases, and in other cases the output will have no reflection of this reality.

Of course, science has means allowing correction of our errors. To receive evidence that an inductive inference is true or false, an additional study is needed (for instance, turn directly to experience and practice, compare the attained inference with other postulates already proved in science). If experience (observation, experiment) intended for verifying the inductive supposition confirms it, it is preserved in the wealth of scientific knowledge; and if it disproves it, the idea is rejected giving full scope to other ideas (hypotheses). In a range of cases a scientist making an erroneous hypothesis subsequently performs an experiment proving or disproving its content. Or, at least, borrows an experiment scheme from his or her colleague. If the experiment conditions exceed the limits of material resources or the level of the science development available at that time, the idea that once emerged is verified by the next generations of researchers.

The need for additional research (experiments) to determine the trueness or falsehood of inductive inference means that artificial intelligence possessing inductive logic in equal measure has to be able to perform similar additional studies. Replying to a question of how experiments proving or disproving some concept are performed, any experimentalist scholar would reply that invention of a new experiment is a creative activity. The history of science demonstrates that the conditions for important experiments are discovered in the same manner as everything new and significant: a) through trial and error (by linear search method), b) as a result of summarizing efficiency of some experimental schemes discovered by other researchers, c) owing to the use of analogy complemented with the synthesis of isolated technological ideas borrowed from different fields.

The author considered the role of analogy in the process of the emergence of new scientific ideas was in his book [10].

All the above demonstrates that when verifying its inductive ideas, artificial intelligence has to perform additional empiric studies involving new experiments and invention of tests enabling to confirm or call in question different theoretical constructs. Since no algorithm for inventing experimental (technological) means exists for verification of new ideas, a computer has to create these means through trial and error (by linear search method) inductively summarizing the efficiency of experimental schemes that are already developed and transferring technological ideas from one field into another on the basis of analogy. If life time of a computer is limited, the task of performing new experiments will have to be solved by other generations of computers with more sufficient material resources at their disposal and a higher level of scientific knowledge.

3.2. Trial and error method

Another factor excluding the possibility of algorithmization of creativity in the field of science is the method of trial and error (linear search method). The trial and error method, or in other words the backward elimination strategy, plays a huge role in scientific research. When information lacks, i.e. there are no original assumptions for inductive generalization, and when there are no ideas (theoretical constructions) enabling to implement analogy and transfer these ideas from one field into another field, there's nothing else left but the method of linear search. Depending on the availability of information this research technique falls into two categories: 1) absolutely blind search presupposing a large-scale check of all possible options not supported by any preliminary information, 2) linear search taking into account previous knowledge, i.e. matching with various guesses and heuristics used to reduce searched options (alternatives). Absolutely blind search means absence of any apparent indicators. In this case, any potential search direction is as promising or, vice versa, not offering anything, as all the others. The blind method of trial and error continuously searches options without any hints (data) regarding the fact whether any of these options will be worth selection and which one that will be. On the contrary, search taking into account previous knowledge doesn't save from mistakes instead it gives an opportunity to correct them in the light of the goals to be achieved. Memories of unsuccessful trials provide us with information on search areas where the solution should not be looked for; this leads to saving material resources and time. Correlation of information obtained at a search stage with already available facts and ideas increases the efficiency of search by virtue of numerous loops of the feedback (feedback can be described as follows: trial → correlation with ideas → trial → correlation with ideas). An actual scientific research utilizes the method of linear search based on the least amount of preliminary information more frequently than the method of absolutely blind search. In his day, Karl Popper, an English philosopher and methodologist of science, paid attention to this fact. In one of the articles published in [11] he writes: "Movements of a seeker won't be fully random. There are various reasons for that – both positive and negative. Positive reasons mainly come down to the fact that the seeker has a problem that he has to solve. This means that he has some knowledge, however foggy it can be, acquired by trial and error. This knowledge is his guide which excludes absolute chance" [11, p.149].

The method of trial and error is used both in the empiric (experimental) field of science and on the level of creation and development of complex theories and concepts representing generalization and synthesis of different experimental facts and ideas. According to Donald Campbell who deeply analyzed the role of the trial and error method in the process of human learning in his essay "Evolutionary Epistemology" [11], on the one side of the scale is an experimenter who uses the heuristics of continuous search depending on the capacity of laboratory equipment and tries to vary each parameter and search all possible combinations paying no attention to the theory. On the opposite side of the scale we see a "natural" selection of scientific theories competing through trial and error in their adequacy to solve various problems, i.e. in adequacy (compliance) of these theories to (with) the total set of accumulated facts.

Scientists who studied the capacities of logic (induction and deduction) in generalization of original assumptions often underlined the fact that no method (procedure) was provided for discovering the assumptions themselves. This opinion is shared by M. Bunge noting in [12] that logical information processing methods leave open the question of availability of such processed and standardized strategy to search facts that are generalized further on. Strange though it may seem, the method of trial and error is such a strategy (linear search method). A large-scale check of all alternatives underpinning this method often turns out to be heavy and consuming considerable material resources and time. However, it is this check that provides scientists with original knowledge necessary for solving problems and with knowledge launching mental processes of induction and analogy.

The history of science abounds with examples of discoveries and inventions made owing to the strategy of linear search (screening) which had as many mistakes as correct steps. Discoveries made owing to the method of trial and error include the law of elliptic planetary motion (Johannes Kepler), the filament for the electric bulb

(Thomas Edison), synthesis of Salvarsan, medicinal treatment for syphilis (Paul Ehrlich, the 1908 Nobel prize), industrial synthesis of ammonia (Fritz Haber, the 1918 Nobel prize), discovery of actinomycin, antibiotic (Selman Waksman, the 1952 Nobel prize), the prove of the four-color theorem (Kenneth Appel and Wolfgang Haken).

With regard to artificial intelligence it means that it has to use the method of trial and error for studying the world around, comprehending its laws, inventing objects and things that don't contradict these laws, and use a technique for solving problems that has no algorithmic properties and doesn't ensure the easiness of achieving the goal. When preliminary knowledge in a new field (beyond the known) is lacking, the computer won't avoid absolutely blind search, i.e. a large-scale check of all possible options with no whatsoever meaningful supporting information. Even if linear search is combined with various assumptions and heuristics implemented for reducing the number of searched options, the computer still won't be able to completely dispose of errors. Memories of failed trials will enable artificial intelligence to have information about unpromising fields of search and save material resources. However, in any form (even if fitted with heuristics), the method of trial and error is an expensive research process. Science created by a human being overcomes some negative aspects of the trial and error method by means of concurrency of search. Concurrency of search means that every day (or even every minute) one and the same problem is studied by hundreds and thousands of people separated by languages, countries, continents, research laboratories scattered all over the world. A considerable number of scientists solving the same tasks often make simultaneous and independent discoveries (history knows many examples of such reoccurring discoveries). To avoid the high degree of "reoccurrence", science managers hold numerous scientific conferences intended for providing timely information to representatives of different research groups on results obtained and for agreeing upon and coordinating further actions. It is needless to say that if artificial intelligence was assigned with a task to match a human being for obtaining important scientific and technical results, a thousand computers possessing inductive logic and ability to withdraw new knowledge from experiments and observations would not suffice. Otherwise, concurrency of search wouldn't yield apparent gains.

Mentioning the method of trial and error again, we shall point out that among the first ones to realize the need to endow artificial intelligence with this method, far beyond the perfection of algorithmic software, was Donald Campbell, an American psychologist, sociologist and philosopher who we have already mentioned. In his essay "Evolutionary Epistemology" presented in [11], D. Campbell underlines that a computer that would generate its own heuristics should do that through blind trials and errors when groping after heuristic principles. And, the selected principles would present accumulated general knowledge [11, p.113]. We can only regret that D. Campbell first expressed this thought in 1974 when S. Smale's 18th problem wasn't defined yet as this thought is directly related to solving this problem.

3.3. Case factor in a scientific discovery

It has long been identified that natural processes cannot be described without using probabilistic representations. This fact leads to the impossibility of accurate prediction of the behavior of the majority of dynamic systems. The degree of stochastic behavior of process in question determines the so-called forecast horizon (limit of predictability) for such systems.

Something of the kind takes place in creative activity. For instance, a high degree of accuracy in forecasting the future of a research discipline is impossible, i.e. one cannot anticipate discoveries to be made in this discipline even possessing extensive information about its current achievements. Sudden, unplanned events that can take place in science don't allow for forecasting all details of development in a specific branch of knowledge.

One of the laser inventors and Nobel laureate in physics Charles Townes writes in [13] that an element of unexpectedness is a component of technological progress and that it's exactly what is incredibly difficult to combine with any conventional principles of planning [13, p.160].

He points out that it is not feasible to plan a new idea and a new, yet unknown technological invention, as it can't be proved that this research area will lead to new technical achievements if the essence of these achievements is still unknown [13, p.160].

The same opinion is shared by Yuval Neeman, an Israeli physicist who together with M.Gell-Mann developed the theory of elementary particles. Discussing the impossibility to accurately forecast and plan scientific achievements in [14], the Israeli physicist addresses the issue of grant distribution. As a rule, a foundation providing a grant requires to submit a request including the plan of projected research and its goals. Apparently, a discovery made by virtue of luck cannot be forecasted. Thus, the most vital results will never be reflected in requests. Consequently, those who provide grants should not treat requests very seriously [14, pp.86-87].

Why is it impossible to plan a discovery with a high degree of accuracy? In other words, what is the reason for certain unexpectedness of new advances in science? The answer to this question is suggested by the history of science: many discoveries are accidental or, at least, conditioned by a certain degree of chance. An opportunity to find something beyond the plans and intentions of a researcher is often given by the abovementioned method of trial and error (linear search method) implementing systematic search of options for solving a specific task. This case is vividly illustrated by the life of Christopher Columbus: he looked for a sea route to India and in actual fact discovered America. If we call such unplanned (unintended) discoveries incidental outcomes of the major research line, we should note that these incidental outcomes suggest solution to quite different tasks not directly related to the problems that initiated the search. Remarkably, it is impossible to rule out incidental discoveries with any amount of information you possess when you start mastering a new field. Indeed, this information is already formalized and recorded knowledge, while creativity implies going beyond the known, beyond the area with reference points and signs.

We have already discussed that the method of trial and error supplies original assumptions (single facts) for the logical operation of induction through which these assumptions are processed. Since linear search of options performed with a certain intention often gives birth to incidental outcomes (accidental discoveries) giving a clue to solving problems that initially were beyond our vision, we should underline that case factor also supplies (is a source of) original assumptions for induction. In other words, we can delineate induction based on the method of trial and error and induction based on the factor of chance. Thus, the probability element typical of incomplete induction is complimented by chance findings providing induction (regardless of the degree of its completeness) with facts to be generalized. Here we have dual probability of inductive logic.

However, we shouldn't be too pessimistic as science is successfully developing notwithstanding these non-algorithmic aspects of inductive thinking. Such scientists as J. Maxwell, L. Boltzmann, H. Poincare, W. Heisenberg, M. Born, E. Lorenz, and I. Prigogine taught us to have a calm attitude towards the probabilistic (stochastic) character of the patterns of the surrounding world. The elements of probability characteristic of the trial and error method granting the non-algorithmic quality can be perceived in the same manner.

Among scientific discoveries greatly influenced by the factor of chance we find the discovery of relationship between electricity and magnetism (Christian Orsted, 1820), invention of photography (Louis Daguerre, 1835), invention of telephone (Alexander Bell, 1875), discovery of electromagnetic waves (Heinrich Hertz, 1886), detection of x-rays (Wilhelm Roentgen, 1895), discovery of radioactivity (Henri Becquerel, 1896), etc.

An example of an accidental discovery that was recently made and awarded the Nobel Prize is discovery of polymers with the ability of metals to conduct an electric current. An essential role in this discovery made by a Japanese chemist Hideki Shirakawa (the 2000 Nobel Prize in Chemistry), was played by an error committed by a post-graduate student in an experiment.

V.A. Marikhin writes in [15]: "And, in 1971, Hideki Shirakawa, professor of Tokyo Institute of Technology, asked his post-graduate student to make polyacetylene. Initially, polyacetylene was synthesized in the form of dark powder in 1955 and it didn't possess any outstanding features. However, the visiting scientist by mistake added the reaction mix catalyzer by 1,000 times exceeding the amount required in accordance with guidelines (perhaps, he confused grams with milligrams). As a result instead of dark powder, wonderful silvery film was formed. Hardly had H. Shirakawa looked at the film, he thought that it could be used for creating polymers with the properties of metal conductors" [15, p.11].

The same is reported by M. Rybalkina in [16]: "How often the history of science sees a discovery aided by chance. Once Shirakawa's student added too much catalyzer and, as a result, colorless plastic all of a sudden became gleaming as silver and that led to an idea that it was no longer nonconductor. Further research resulted in discovery of polymer with conductivity exceeding that of conventional plastic by tens of millions of times. This opens the door to new electronics of the XXI century based on organic materials" [16, p.187].

From the point of view of the scientific research methodology it goes without saying that such mistakes leading to discoveries cannot be forecasted and planned in advance.

The reader will find a description of a large number of random discoveries made on the principle of "serendipity" in the author's monograph [17].

Solving S. Smale's problem with regard to the limits of natural and artificial intelligence, we have to keep comparing the cognitive activity of a human being with that of computers. What results can we arrive at making such a comparison if we know that the factor of chance plays an essential role in scientific (creative) search? The answer we propose can seem paradoxical; however, it logically follows the actual state of things: artificial intelligence has to be able to make accidental discoveries. It needs to acquire the ability to obtain unplanned (unintended) scientific results as incidental outcomes of research. Solving a certain problem and encountering a situation when facts (data) containing the solution to a completely different task are found incidentally, it should dramatically change the area of research rejecting previous hypotheses if they don't agree with the information learnt owing to an accidental unexpected discovery.

The factor of chance in scientific search often determining its success (effectiveness) is the climax of non-algorithmic (non-computable) nature of creative process.

3.4. Gödel's incompleteness theorem

In his lecture "Mathematical Problems for the Next Century" [1] S. Smale states a problem of identifying the limits of human and artificial intelligence referring to R. Penrose's monograph "The Emperor's New Mind" [18]. In the first place, S. Smale pays attention to the analysis of Gödel's incompleteness theorem conducted by R. Penrose. R. Penrose reminds that Gödel's incompleteness theorem gave a negative answer to D. Hilbert's question regarding the possibility to prove compatibility of arithmetic axioms based upon the axioms themselves.

K. Gödel (1931) demonstrated that any formal arithmetic system of axioms and rules of inference should include predicates which are neither provable nor refutable within this system. Originally, Gödel's result had been related to arithmetic but subsequently it was generalized to cover all formal systems not necessarily arithmetic ones. By the merit of Alfred Tarski and his school this generalization was made. And, this is mentioned by L.D. Beklemishev in [19].

It should be noted that K. Gödel himself guessed that his incompleteness theorem pertained not only to arithmetic. In [20] A.M. Khazen gives an abstract wording of the incompleteness theorem suggested by K. Gödel himself: "A complete epistemological description of a language A cannot be given in the same language A, because the concept of truth of sentences in A cannot be defined in A" [20, p.281].

Considering Gödel's incompleteness theorem in its generalized wording, R. Penrose sees the proof that there's no mechanic procedure (set of rules) for solving all problems notwithstanding their complexity. Taking into account the fact that mathematicians discover theorems and then look for their proof with no universal algorithm at their disposal that contains the criteria of truth, R. Penrose comes to the conclusion that our consciousness has a substantially non-algorithmic component.

Thus, human intelligence cannot be properly modeled (described) with rigorous algorithms having no space for uncertainty and probability. In R. Penrose's opinion, Gödel's incompleteness theorem is a limitation both for human intelligence and those computers that we hope to endow with signs of "reason" one day.

How should this limitation be interpreted? To answer this question, we should pay attention to the fact that Gödel's theorem is related to closed formal systems (closed algorithms). Since the fundamental objective of science is to study the surrounding world through various trials and experiments, it is easily seen that a closed formal system is any system that doesn't gain relevant information from trial and experiment. In principle, having stated the incompleteness theorem that gave a negative solution to D. Hilbert's problem, K. Gödel attracted our attention to the fact that any algorithms (algorithmic systems) aimed at studying the world around cannot be effective if they are closed.

Many authors write that limitations apparent from Gödel's results apply only to closed formal systems. A.S. Potapov writes in [21]: "…Many arguments are not applicable to open continuous algorithmic systems (or embodied intelligence). In particular, for such systems the proof of insolubility of the halting problem (and its numerous implications) turn out to be invalid, as well as Gödel's theorems posing limitations to the capacity of formal systems turn out to be inapplicable. Augmentation of unattainability of the function of understanding partially just for closed systems turn out to be invalid with regard to systems forming concepts as a result of interaction with the real world" [21, p.702].

The same is mentioned by A.N. Kochergin in his article [22]: "There is a substantiated opinion that limitations implied by Gödel's theorem apply only to Turing machines receiving no information from the environment. Given the machine receives information from the environment that is an infinite information system, it appears capable of solving non-constructive problems the algorithmic insolubility of which could be proved" [22, p.215].

If there are ways to remove limitations implied by Gödel's incompleteness theorem on human thinking and activity of computers, why then does Gödel's result still remain one of the principles enabling to give a correct answer to the American mathematician S. Smale's question regarding limits of human and artificial intelligence? Because Gödel's incompleteness theorem is among the factors excluding the possibility of rigorous algorithmization of creative activity in the field of science (and not only in this field). If it were not for this theorem reflecting key peculiarities of human learning, laws of nature could be perceived without trial and experiment, i.e. the outside world would be studied following a universal algorithm containing in itself the assurance of the validity of obtained results. Meanwhile, such universal method is unknown therefore scientists have to study the world around using the method of trial and error (linear search method) frequently encountering unintended and unplanned discoveries and inductively generalizing single facts into hypotheses and ideas that are constantly checked by means of observation and experiment. As we have already highlighted, the need for such checks is related to the probabilistic nature of inductive conclusion, i.e. to the fact that inductive inference doesn't often cover the entire set of elements related to the aggregate regarding which we are making a generalizing conclusion.

Artificial intelligence that will function owing to the processes of self-learning instead of rigid computer software will have to master the same procedures for acquiring new knowledge: large-scale search of options, inductive strategy for information processing, and art of finding one thing while looking for another (by the method of accidental discoveries). Without self-learning processes and continuous experience accumulation, artificial intelligence won't be able to overcome limitations implied by Gödel's incompleteness theorem restricting effective functioning of closed algorithmic (non-learning) systems. Figuratively speaking, Gödel's incompleteness theorem itself, or rather limitations connected with it, make us take the track of creating computers capable of learning.

Modern informatics defines two forms of learning: with and without a teacher. Of course, a computer must master the form of learning without a teacher, because this form is the most complicated and has broader options. Indeed, this is the type of learning that enables to obtain something really new. As A.S. Potapov notes "as a matter of fact, a considerable part of scientific research can be viewed as learning without a teacher (or, at least, as reinforcement learning). Where can an informed teacher appear from if solutions are unknown to any of the people and only nature can be asked whether the solution is correct and only when there is a possibility to go beyond pure observations and make a correct experiment?" [21, p.224].

4. Solving S. Smale's 18th problem

So, what awaits artificial intelligence when it comes close to the perfection of the human brain in such parameters as sensory perception, memory, language, and complex motor actions? Obviously, it will face the same limits that are characteristic of human learning. As we have already found out, these limits are four factors: Gödel's incompleteness theorem, probabilistic nature of inductive inference, the method of trial and error and the factor of chance in scientific discovery. The identified factors excluding the possibility of algorithmization of creative activity in the field of science give solution to the 18th problem suggested by the American mathematician S. Smale in his lecture "Mathematical Problems for the Next Century" [1].

Gödel's incompleteness theorem proves that algorithms (procedures, methods, techniques) of researching reality cannot contain the criteria of truth. These criteria of truth are found in practice (observation and experiment). Gödel's result restricts effective functioning of closed algorithmic strategies. That is why Gödel found that D. Hilbert's problem of proving the compatibility of arithmetic by means of arithmetic itself is insoluble.

The probabilistic nature of inductive inference implies that the logical operation of induction in some cases gives the truth and in other cases it can lead to errors. At some point, this aspect attracted G. Leibniz's attention. He rejected induction and started looking for a universal method of discovery ("universal characteristic") able to ensure a correct result. But, such method (the rule of application of all rules) doesn't exist which was already suspected by Immanuel Kant who was skeptical about G. Leibniz's dream of "a universal characteristic". Induction ranks below deductive thinking in rigor, validity and cogency, but, nonetheless, provides us with new knowledge. It should also be taken into account that owing to inductive generalization of creative activity tens of hundreds of various heuristics enhancing our capabilities in solving scientific and technological tasks have been discovered.

As we have already noted, the method of trial and error (linear search method) plays a titanic role in scientific research. When there is no information, i.e. original assumptions for inductive generalization, and when there are no ideas (theoretical constructions) enabling to draw analogy, the method of linear search is what is left. The method of trial and error is applied both in empiric (experimental) field of science and on the level of creation and development of complex theories and concepts representing generalization and synthesis of different experimental facts and ideas.

Finally, the factor of chance in scientific discovery is another irremovable peculiarity of human learning. Incidental or “semi-incidental” discoveries cannot be ruled out no matter how much information you have when you start mastering a new area of knowledge. This information is already formalized and recorded knowledge while creativity implies going beyond the known, beyond the area with reference points and signs. The factor of chance (the element of unpredictability of certain scientific search aspects) along with the method of trial and error supplies original assumptions for induction.

Unpredictability of scientific discoveries conditioned by chance factor has its aesthetic aspects. Creativity and the birth of something new is impossible in the world where all events are fatally predetermined (destined) and it is known in advance what is going to happen in ten or thousand years. It bears reminding that negative impact of the fact that scientific research depends on the factor of chance is overcome by the factor of time and concurrence of search which we have already mentioned. The more time is spent on solving a problem and the more researchers are involved, the higher is the probability of obtaining a result.

5. Conclusion

It is surprising that being a mathematician and formulating exceptionally mathematical problems (still unsolved) in his list, S. Smale raised a question of establishing the limits of natural and artificial intelligence which is much closer related to informatics than mathematics. Of course, Gödel's incompleteness theorem as one of the factors excluding the algorithmic character of creativity, surely, belongs to the field of mathematics but this theorem alone doesn't solve S. Smale's 18^{th} problem. There are three other similar factors (listed above) that endow creative activity with signs of non-computability and non-formalizability. Identifying the role of these factors in scientific creativity requires the use of outcomes in such fields of knowledge as cognitive psychology, neurophysiology, logic, history of scientific discoveries, and theory of artificial intelligence.

However, it should not be surprising that the problem posed in one area of knowledge is often solved by methods borrowed from very different areas. For example, G. Perelman (2002) proved H. Poincare's hypothesis and thus solved S. Smale's second problem (a purely topologic problem) using Hamilton's Ricci flow, this method belongs to the sphere of mathematical physics and not to topology.

References

1. Смейл С. Математические проблемы следующего столетия // сборник «Современные проблемы хаоса и нелинейности», Ижевск, Институт компьютерных исследований, 2002. - С.280-303.

2. Хокинс Дж., Блейксли С. Об интеллекте. – М.: «Вильямс», 2007. - 240 с.

3. Ушакова Т.Н. Психолингвистика. – М.: ПЕР СЭ, 2006. - 416 с.

4. Люгер Дж. Искусственный интеллект. – М.: «Вильямс», 2003. – 864 с.

5. Дмитриев А. Хаос, фракталы и информация // Наука и жизнь. – 2001. - № 5. - С.44-52.

6. Рассел С., Норвиг П. Искусственный интеллект: современный подход. – М.: «Вильямс», 2006. – 1408 с.

7. Гейм А. Случайные блуждания: непредсказуемый путь к графену // Успехи физических наук. – 2011. - Том 181, № 12. - С.1284-1298.

8. Рассел Б. Человеческое познание: его сфера и границы – М.: «Республика», 2000. – 464 с.

9. Пойа Д. Математика и правдоподобные рассуждения. – М.: «Наука», 1975. - 464 с.

10. Новиков Н.Б. 1000 аналогий, изменивших науку. – М.: Институт психологии РАН, 2010. – 878 с.

11. Эволюционная эпистемология и логика социальных наук. Составители: Д.Г. Лахути, В.Н. Садовский, В.К. Финн. – М.: Едиториал УРСС, 2000. – 464 с.

12. Бунге М. Интуиция и наука. – М.: «Прогресс», 1967. – 187 с.

13. Таунс Ч. Квантовая электроника и технический прогресс // Успехи физических наук. – 1969. - Том 98, № 1. - С.159-169.

14. Нееман Ю. Счастливый случай, наука и общество. Эволюционный подход // Путь (международный журнал). – 1993. - № 4. - С.70-90.

15. Марихин В.А. Синтетические металлы // Химия и жизнь. – 2000. - № 6. - С.11-13.

16. Рыбалкина М. Нанотехнологии для всех. – М.: изд-во «Nanotechnology News Network», 2005. – 444 с.

17. Новиков Н.Б. 18-я проблема С.Смейла в зеркале случайных открытий. – М.: Институт психологии РАН, 2017. – 1390 с.

18. Пенроуз Р. Новый ум короля. – М.: Едиториал УРСС, 2003. – 384 с.

19. Беклемишев Л.Д. Теоремы Геделя о неполноте и границы их применимости // Успехи математических наук. – 2010. - Том 65, № 5 (395). - С.61-106.

20. Хазен А.М. О возможном и невозможном в науке. – М.: «Наука», 1988. – 384 с.

21. Потапов А.С. Искусственный интеллект и универсальное мышление. – СПб., «Политехника», 2012. – 711 с.

22. Кочергин А.Н. Искусственный интеллект, психика и творчество // сборник статей «Искусственный интеллект: междисциплинарный подход», редакторы – Д.И. Дубровский и В.А. Лекторский, Москва, «ИИнтеЛЛ», 2006, с.209-222.