Cognitive dynamic logic algorithms for situational awareness

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ABSTRACT

Autonomous situational awareness (SA) requires an ability to learn situations. It is mathematically difficult because in every situation there are many objects nonessential for this situation. Moreover, most objects around are random, unrelated to understanding contexts and situations. We learn in early childhood to ignore these irrelevant objects effortlessly, usually we do not even notice their existence. Here we consider an agent that can recognize a large number of objects in the world; in each situation it observes many objects, while only few of them are relevant to the situation. Most of situations are collections of random objects containing no relevant objects, only few situations "make sense," they contain few objects, which are always present in these situations. The training data contains sufficient information to identify these situations. However, to discover this information all objects in all situations should be sorted out to find regularities. This "sorting out" is computationally complex; its combinatorial complexity exceeds by far all events in the Universe. The talk relates this combinatorial complexity to Gödelian limitations of logic. We describe dynamic logic (DL) that quickly learns essential regularities—relevant, repeatable objects and situations. DL is related to mechanisms of the brain-mind and we describe brain-imaging experiments that have demonstrated these relations.

Keywords: cognitive algorithms, situational awareness, complexity, logic, Gödel, dynamic logic, learning

1. INTRODUCTION: COMPLEXITY AND LOGIC

Object perception involves signals from sensory organs and internal mind's representations (memories) of objects. During perception, the mind associates subsets of signals corresponding to objects with representations of object. This produces object recognition; it activates brain signals leading to mental and behavioral responses, parts of understanding.

Mathematical descriptions of the very first recognition step in this seemingly simple association-recognition-understanding process has not been easy to develop, a number of difficulties have been encountered during the past fifty years. These difficulties were summarized under the notion of combinatorial complexity (CC)[1]. CC refers to multiple combinations of various elements in a complex system; for example, recognition of a scene often requires concurrent recognition of its multiple elements that could be encountered in various combinations. CC is prohibitive because the number of combinations is very large: for example, consider 100 elements (not too large a number); the number of combinations of 100 elements is 100^{100}, exceeding the number of all elementary particle events in life of the Universe; no computer would ever be able to compute that many combinations. Learning situations is no less difficult than learning objects. Even assuming that an agent can recognize objects, and that situations are subsets of objects, still recognizing situations involves sorting through astronomical number of subsets of objects.

The problem was first identified in pattern recognition and classification research in the 1960s and was named "the curse of dimensionality"[2]. It seemed that adaptive self-learning algorithms and neural networks could learn solutions to any problem 'on their own', if provided with a sufficient number of training examples. The following thirty years of developing adaptive statistical pattern recognition and neural network algorithms led to a conclusion that the required number of training examples often was combinatorially large. Thus, self-learning approaches encountered CC of learning requirements.

Rule-based systems were proposed in the 1970's to solve the problem of learning complexity[3,4]. An initial idea was that rules would capture the required knowledge and eliminate a need for learning. However in presence of variability, the number of rules grew; rules became contingent on other rules; combinations of rules had to be considered; rule systems encountered CC of rules.

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Beginning in the 1980s, model-based systems were proposed. They used models which depended on adaptive parameters. The idea was to combine advantages of rules with learning-adaptivity by using adaptive models. The knowledge was encapsulated in models, whereas unknown aspects of particular situations were to be learned by fitting model parameters[5],[6]. Fitting models to data required selecting data subsets corresponding to various models. The number of subsets, however, is combinatorially large. A general popular algorithm for fitting models to the data, multiple hypothesis testing[5], is known to face CC of computations. Model-based approaches encountered computational CC (N and NP complete algorithms).

In subsequent research, CC was related to the type of logic, underlying various algorithms and neural networks[1]. Formal logic is based on the "law of excluded middle," according to which every statement is either true or false and nothing in between. Therefore, algorithms based on formal logic have to evaluate every little variation in data or internal representations as a separate logical statement (hypothesis); a large number of combinations of these variations causes CC. In fact, CC of algorithms based on logic is related to Gödel theory: it is a manifestation of the inconsistency of logic in finite systems[7]. Multivalued logic and fuzzy logic were proposed to overcome limitations related to the law of excluded third[8]. Yet the mathematics of multivalued logic is no different in principle from formal logic, "excluded third" is substituted by "excluded n+1." Fuzzy logic encountered a difficulty related to the degree of fuzziness, if too much fuzziness is specified, the solution does not achieve a needed accuracy, if too little, it will become similar to formal logic. Complex systems require different degrees of fuzziness in various elements of system operations; searching for the appropriate degrees of fuzziness among combinations of elements again would lead to CC. Is logic still possible after Gödel? Bruno Marchal recently reviewed the contemporary state of this field[9], it appears that logic after Gödel is much more complicated and much less logical than was assumed by founders of artificial intelligence. Also, CC is still unsolved within logic. Penrose thought that Gödel's results entail incomputability of the mind processes and testify for a need for new physics[10]. An opposite position in this paper is that incomputability of logic does not entail incomputability of the mind. Logic is not the basic mechanism of the mind.

Various manifestations of CC are all related to formal logic and Gödel theory. Rule systems rely on formal logic in a most direct way. Self-learning algorithms and neural networks rely on logic in their training or learning procedures: every training example is treated as a separate logical statement. Fuzzy logic systems rely on logic for setting degrees of fuzziness. CC of mathematical approaches to the mind is related to the fundamental inconsistency of logic.

2. DYNAMIC LOGIC

Dynamic logic maximizes a similarity measure between models, $\mathbf{M}_m$ and signals $\mathbf{X}(n)$ by fitting model parameters to signal. In neural terminology, models are mental representations, sources of top-down signals, and bottom-up signals, $\mathbf{X}(n)$, come from sensor organs. Higher in the mind hierarchy, bottom-up signals come from activated mental representations-models at lower levels. Similarity at a single level of interacting bottom-up and top-down signals is given by[11]

$$L(\{\mathbf{X}\},\{\mathbf{M}\}) = \prod_{n\in N} \sum_{m\in M} r(m)\, l(\mathbf{X}(n) \mid \mathbf{M}_m). \tag{1}$$

Here, $l(\mathbf{X}(n) \mid \mathbf{M}_m)$, or $l(n|m)$ for shortness, is a conditional similarity of signal $\mathbf{X}(n)$ given that it originates from model (object, event) $\mathbf{M}_m$. The similarity structure follows standard probabilistic rules with multiple models: each model is an alternative for each signal, and the similarity sums over alternatives; signals are evidence and all should be accounted for, hence is the product. Conditional similarities, for convenience, are normalized on the object (event) m being definitely present; the actual probability of m being present is modeled by coefficients r(m). Probabilistic analogy of (1) suggests interpreting as independent errors between signals and their model predictions. Similarity between models and signals is a measure of knowledge accumulated by the agent about the world. Therefore maximization of similarity is a mathematical model of the knowledge instinct[12] also called need for cognition or need for knowledge.

Similarity (1) contains M^N items. This combinatorially large number (more than any astronomical number) is the reason for CC of mathematical algorithms in the past. The DL learning process consists in estimating model parameters $\mathbf{S}_m$ and associating subsets of signals with models-representations by maximizing the similarity (1). Although (1) contains combinatorially many items, DL maximizes it without combinatorial complexity[11],[12],[13],[14],[15],[16]. First, fuzzy association variables f(m|n) are defined,

$$f(m|n) = r(m)\, l(n|m) \,/\, r(m')\, l(n|m'). \tag{2}$$

These variables give a measure of correspondence between signal $\mathbf{X}(n)$ and model $\mathbf{M}_m$ relative to all other models, m'. They are defined similarly to the a posteriori Bayes probabilities, they range between 0 and 1, and as a result of learning they converge to the probabilities under certain conditions. Second, the DL process is defined by the following set of differential equations,

$$df(m|n)/dt = f(m|n) \sum_{m' \in M} \{[\delta_{mm'} - f(m'|n)]\ [\partial \ln l(n|m')/\partial \mathbf{M}_{m'}]\ (\partial \mathbf{M}_{m'}/\partial \mathbf{S}_{m'})\ d\mathbf{S}_{m'}/dt,\ \ \delta_{mm'} = 1 \text{ if } m=m', 0 \text{ otherwise},$$

$$d\mathbf{S}_m/dt = \sum_{n \in N} f(m|n)[\partial \ln l(n|m)/\partial \mathbf{M}_m]\partial \mathbf{M}_m/\partial \mathbf{S}_m. \tag{3}$$

These differential equations can be solved iteratively. The iterations could begin with any values of the unknown parameters $\{\mathbf{S}_m, r(m)\}$; at every iteration step, the first of the above equations can be substituted by eq.(2), and new values of parameters are computed by a step defined by the second of the above equations. Iteration continue until parameter changes decrease below a set limit. A theorem was proved that this procedure converges.

A salient feature of this DL process is that parameters defining vagueness of conditional similarities (parameters such as covariances) initially are set in correspondence to uncertainty in parameter values (we return to this later). During iterations, parameters become more precise, models better fit patterns in the signals, and vagueness decreases. This is the reason to call the DL learning a process "from vague to crisp."[17],[18],[19],[20].

3. DL FOR SITUATIONAL AWARENESS

We consider now learning situations as sets of objects. The problem of object recognition has not been solved and we return to it later. Here, the task for an intelligent agent (or a child) is to learn situations in the environment. For example, situation "office" is characterized by the presence of a chair, a desk, a computer, a book, a bookshelf. The principal difficulty is that many irrelevant objects are present in every situation.

In the example below, D_o is the total number of objects that the agent can recognize in the world (it is a large number). In every situation the agent perceives D_p objects. This is a much smaller number compared to D_o. Each situation is also characterized by the presence of D_s objects essential for this situation. Normally nonessential objects are present and Ds is therefore less than D_p ($D_s << D_p << D_o$). The sets of essential objects for different situations may overlap, with some objects being essential to more than one situation. The real life learning is sequential as a child is exposed to situations one at a time. DL can handle this, but in this paper we consider the data about all the situations available at the time of learning.

Following[21], a situation can be mathematically represented as a vector in the space of all objects, $X_n = (x_{n1}, \dots x_{ni}, \dots x_{nDo})$. If the value of x_{ni} is one the object i is present in the situation n and if x_{ni} is zero, the corresponding object is not present. Since D_o is a large number, X_n is a large binary vector with most of its elements equal to zero. A situation model is characterized by its parameters, a vector of probabilities, $p_m = (p_{m1}, .. p_{mi}, ... p_{mDo})$. Here p_{mi} is the probability of object i being part of the situation m. Thus a situation model contains D_o unknown parameters. Estimating these parameters constitutes learning situations.

We model the elements of vector p_m as independent (this is not essential for learning, if presence of various objects in a situation actually is correlated, this would simplify learning, e.g. perfect correlation would make it trivial). Correspondingly, conditional probability of observing vector X_n in a situation m is then given by the standard formula (Jaynes 2003).

$$l(\mathbf{X}(n)\ |\ \mathbf{M}_m(n)) = \prod_{i=1}^{Do} p_{mi}^{\ x_{ni}} (1 - p_{mi})^{(1-x_{ni})}. \tag{4}$$

Consider N perceptions a child or agent was exposed to, among them most perceptions were "irrelevant" corresponding to observing random sets of objects, and M-1 "real" situations, in which D_s objects were repeatedly present. All random observations we model by 1 model ("noise"); assuming that every object has an equal chance of being randomly observed in noise (which again is not essential) the probabilities for this noise model, m=1, are p_{1i}=0.5 for all i. Thus we define M possible sources for each of the N observed situations.

The total likelihood-similarity for our M models (M-1 "real" and 1 noise) is given by the same eq.(1); and the same DL eqs.(2, 3) maximize it over the parameters, which in this case are the probabilities of objects constituting various situations. The parameter estimation eq.(3) in this case can be significantly simplified[21],

$$p_{mi} = \sum_{n \in N} f(m|n)\, x_{ni} \Big/ \sum_{n' \in N} f(m|n'). \tag{5}$$

In the example below we set the total number of objects to D_o=100; the number of objects observed in a situation D_p = 10; in situations important for learning there are 5 objects characteristical of this situation, D_s = 5; in clutter situations, D_s = 0. There are total of 10 important situations, each is simulated 25 times; in each simulation D_s = 5 characteristic objects are repeated and the other 5 selected randomly. This yields a total of 250 situations. We also generated 250 clutter situations, in which all objects are randomly selected. This data is illustrated in Fig. 2. The objects present in a situation (x=1) are shown in white and absent objects, x=0, are shown in black. In this figure objects are along the vertical axes and situations are along the horizontal axes; situations are sorted, so that the same situations are repeated. This results in horizontal white lines for characteristic objects for the first 10 situations.

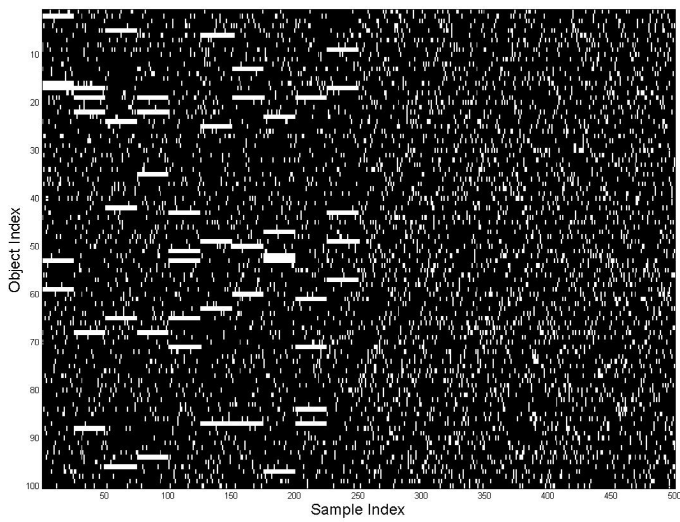

Fig. 1. The objects present in a situation (x=1) are shown in white and absent objects (x=0) are shown in black. In this figure objects are along the vertical axes and situations are along the horizontal axes; situations are sorted, so that the same situations are repeated. This results in horizontal white lines for characteristic objects for the first 10 situations (each repeated 25 times).

In real life situations are not encountered sorted. A realistic situation is shown in Fig. 2, in which the same data are shown with situations occurring randomly. The DL iterations are initiated as described in the previous section. The number of models is unknown and was set arbitrarily to 20. It is possible to modify DL iterations so that situations are initiated as needed but it would be difficult to present such results in the paper. Even so the total number of models was set incorrectly, DL converged fast, with 10 models converging to the important models and the rest converging to clutter models. The convergence results are shown in Fig. 3, illustrating the initial vague models and their changes at iterations 1, 2, and 10.

Each column in Fig. 3 illustrates all 20 models, along the horizontal axes, and objects are shown along the vertical axes as in previous figures. The last column (10*) shows iteration 10 resorted along the horizontal axes, so that the 10 models most similar to the true ones are shown first. One can see that the left part of the figure contains models with bright pixels (characteristic objects) and the right part of the figure is dark (clutter models). In the next section we illustrate this fast convergence numerically, along with studying the language effect.

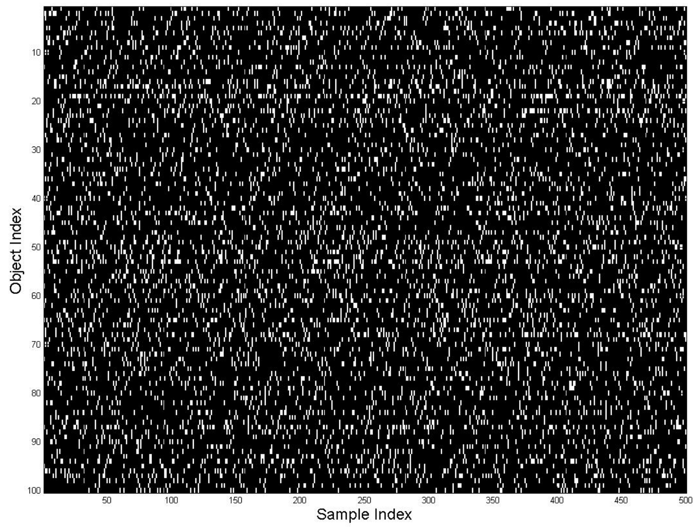

Fig. (2). Same data as in Fig. 2, with situations occurring randomly.

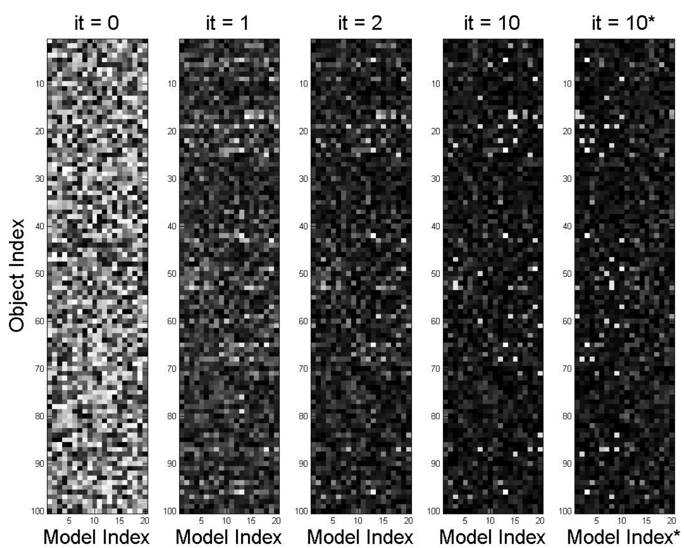

Fig. (3). The convergence results are shown in 5 columns; the first one illustrates the initial vague models and the following show model changes at iterations it = 1, 2, and 10. Each column here illustrates all 20 models, along the horizontal axes, and objects are shown along the vertical axes as in previous figures. The last column (10*) shows iteration 10 sorted along the horizontal axes, so that the 10 models most similar to the true ones are shown first. One can see that the left part of the figure contains models with bright pixels (characteristic objects) and the right part of the figure is dark (clutter models).

Performance of this learning of situations is illustrated in Fig. 4. In this figure convergence is measured using the total similarity between the data and models (lower part of the figure) and using errors between the model probability and data (the upper part of the figure; for every situation the best matching model is selected). Two performance lines indicate results of a first step toward future goal of combining language and cognition. Lines with black dots illustrate the performance of the case considered in the previous section without language effects. Lines with open circles indicate a performance with language supervision: for each situation, 1 of the 25 simulations came with a word-label, so that important situations were easier to separate from one another and from random clutter situations. The performance is good in both cases, convergence occurs in 3-4 iterations. As expected the partial language supervision leads to better learning illustrated in Fig. 4.

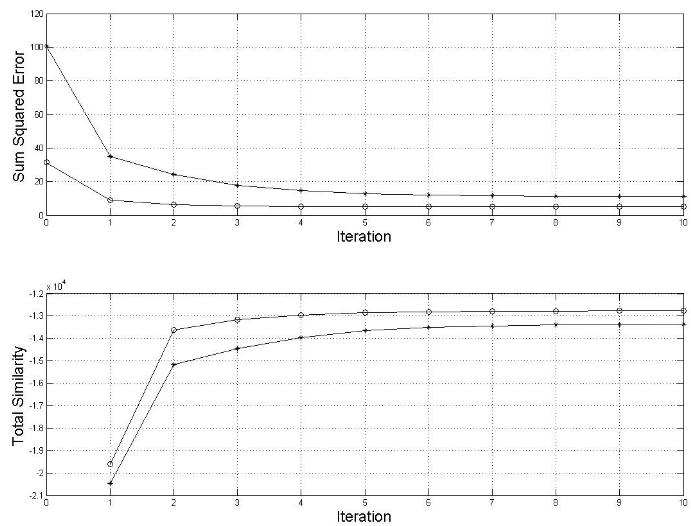

Fig. 4. Top: performance as measured by the similarity measure. Bottom, performance as measured by the average square error. Lines with black dots illustrate the performance of the case considered in the previous section without language supervision. Lines with open circle indicate performance with partial language supervision. In each case performance is good, convergence is attained within few iterations, and language supervision improved performance, as expected.

For shortness, we did not discuss relations among objects. Spatial, temporal, or structural connections, such as "to the left," "on top," or "connected" can be easily added to the above DL formalism. Relations and corresponding markers (indicating which objects are related) are no different mathematically than objects, and can be considered as included in the above formulation. The formulation here assumes that all the objects have already been recognized, but the above formulation can be applied without any change to real, continuously working brain with multiplicity of concurrently running cognitive processes at many levels, feeding each other. The bottom up signals do not have to be definitely recognized objects, these signals can be sent before objects are fully recognized, while object-recognition processes are still running and object representations are vague; this would be represented by x_{ni} values between 0 and 1. Also, the above description is not tied to object-situation relations, it can be equally applied to modeling interactions between bottom-up and top-down signals at any level in the brain-mind hierarchy. The presented formalization therefore is a general mechanism modeling cognitive processes.

4. DISCUSSION

The above example demonstrates a solution to the SA problem, unsolvable for decades. In this section, first we briefly discuss other long-standing problems that have been solved by DL. We also discuss emerging engineering problems, that have not even been considered before DL. These illustrate the reason why DL has been called a mathematical breakthrough. Second, we discuss cognitive brain-mind mechanisms modeled by DL, which could not have been understood for decades. Some of them have been demonstrated experimentally to model actual brain mechanisms, other results in a wealth of experimentally verifiable predictions. This illustrates the reason why DL has been called a cognitive breakthrough. We address a rarely posed question: why some theories and developments are immediately accepted and recognized, whereas others wait for decades and centuries for acceptance and recognition. This fact of the evolution of science and engineering is of significant importance for engineering and scientific communities, it is well known but it has never been understood. It has been addressed by philosophers of science but never by scientists. One consequence of the DL modeling brain mechanism is a first scientific explanation for this phenomenon. Then we discuss unsolved problems and future research directions.

4.1 Long-standing engineering problems

An important application area is clustering[22]. DL clustering requires Gaussian functions to be used for l(n|m)[11],[14] (see also open source publications in[23]). When and $\mathbf{X}(n)$, $\mathbf{M}_m$ are points in a multi-dimensional feature space, eqs.(3) lead to a Gaussian Mixture (GM) clustering. Although GM clustering has been considered in open literature[24] prior to the DL open publications, GM clustering has not been considered practically useful, because of problems with local convergence and for other reasons[25],[22]; According to Fukunaga[26], DL demonstrated that GM can be practically useful. It also enabled derivation of Cramer-Rao Bounds (CRB) for clustering[27]. Any mixture model can be used within DL formalism. If in addition to sources of interest, random sources of signals of no interest are also present, using clutter model with a uniform distribution in feature space would greatly improve result, especially if clutter is dense[11]. Clustering is used when there is no knowledge about expected structures in data. However, usually there is some knowledge, or at least intuition about expected data structures, and DL enables to transform these vague knowledge or intuitions into mathematical formulation and significantly improve clustering according to subjective criteria of the scientist.

Another important classical application is tracking. From the DL point of view, the difference between tracking and clustering is in the models. Whereas in clustering the models $\mathbf{M}_m$ are points (vectors) in multidimensional feature spaces, in DL tracking models describe tracks in 2 or 3 dimensional geometric coordinate spaces. This view on tracking as clustering has been revolutionary, when first published in 1991 (see references in[11]). It led to breakthrough improvements for tracking in clutter, to maximum likelihood tracking in strong clutter, and enabled derivation of Cramer-Rao Bounds (CRB) for tracking in clutter, all of these have been previously considered impossible[28],[29],[30]. Tracking in clutter have to be performed jointly with association, so called "track-before-detect." This problem is often considered NP-complete and therefore unsolvable[5]. DL tracker[31] improved practical performance by two orders of magnitude (9,000% in S/C) and achieved the information-theoretic limit of the CRB. Multiple hypotheses tracking and other combinatorially complex algorithms such as particle filters (which consider tracking and association as separate parts of the problem) are more complex than DL in implementation and inferior in performance by orders of magnitude. DL has also been applied to ATR[32] and to previously unsolved transient signal problems, such as phoneme identification.[33]

Another classical important engineering area addressed by DL is fusion of signals from multiple sensors, platforms, or data bases.[34] In dense clutter, detection, tracking, and fusion have to be performed concurrently, sometimes it is called "fuse-before-track" or "fuse-before-detect," these problems are usually considered unsolvable because of CC. Similar situation exists in data mining; when mining multiple data bases, how the algorithm would know that a word or phrase in one data base is related to a telephone call in another data base. Data and models may include geometric measurements, classification features (feature-added fusion), and other types of information.[35] Problems of this level of difficulty have never been previously considered, and there is no other algorithm or neural network capable of solving them.

An emerging area of engineering, design of Internet search engines, has been considered in[36],[37]. Everyone is familiar with frustrations of using Yahoo or Google, because they do not understand what a user really wants. These references consider how to model language understanding (and learning). The inability so far to engineer natural language understanding, after more than 30 years of efforts, is related in these papers to CC of the problem, and an extension of DL to language learning is developed.[38],[39],[40] A next step to higher intelligence involves integrating language with cognition [41],[42],[43].

Even more intelligent human-computer communication areas emerge. Future computer systems would be able to communicate with humans emotionally as well as conceptually. Current "emotional" toys and robots simulate emotional look-alike without having any mechanisms resembling human (or animal) emotions. DL has been extended to modeling human mechanisms of emotions and their role in cognition[44],[45],[46].

Developing future interacting systems requires understanding of the role of aesthetic emotions of beautiful in cognition. Contemporary aesthetic and cognitive theories are at a complete loss when facing this problem. Similarly, the role of music in cognition has remained a mystery. Approaching these problems is possible with DL.[47],[48],[49],[50],[51],[52]

Another emerging area of engineering is modeling cultures and their evolution. Misunderstanding among cultures is possibly the most significant problem facing the humankind in the 21st century. DL has been extended to modeling cultures; it has been demonstrated that differences in language emotionalities could be an important mechanism of different cultural evolutionary paths, and a joint psycholinguistic and mathematical modeling research area was outlined along with approximate solutions.[53],[54],[55],[56] Existent experimental evidence supports these ideas[57]. Several neuro-imaging laboratories are working on more detailed verification of this theory.

4.2 Structure of scientific revolutions

Understanding how knowledge evolve and gets accepted is essential for improving success of the entire scientific and engineering enterprise. And nevertheless it is rarely addressed, and even if addressed, it is not by scientists or engineers, but by philosophers. In 1962 Thomas Kuhn[58], revolutionized the way scientists and philosophers thought about evolution of scientific knowledge. He argued that new ideas prevail over old ideas not because of the strength of logical arguments or experimental evidence. Scientists or engineers that learned the old ways in school and published books and papers inspired in their youth by old ideas, never change their minds, and would maintain their old way ignoring new discoveries theoretical or experimental. The main factor in change of ideas is time. When the old generation retires and a new generation occupies professorial chairs, then new ideas have a chance.

Kuhn's influential arguments, however, have not explained why some important discoveries become immediately recognized and adopted by engineering community, whereas other immensely important discoveries remain misunderstood and unaccepted for years. I would name just few pairs of ideas, addressing same area of knowledge in about the same timeframe. Aristotelian logic and logic-based AI was readily accepted, whereas Aristotelian theory of the mind, Zadeh's fuzzy logic, Grossberg's neural theories waited for decades. Einstein made three revolutionary discoveries: special theory of relativity, quantum nature of light, and general theory of relativity. Even so he was an acknowledged scientific revolutionary and his discoveries where immediately proven experimentally, he waited almost two decades for his first and the only Nobel Prize, awarded for the least of the three discoveries. Tversky and Kahneman[59] worked for half a century, and Tversky died before the Nobel Prize was awarded in 2002 for their decade's old discovery. The Gödelian theory has been recognized in mathematics overnight, but its implications for cognition and mathematical modeling of the mind are still ignored. This list can be easily multiplied.

DL suggests that existing knowledge of the mind functioning and its models is ready to consider this question as a part of science and engineering. The novel research direction proposed here considers acceptance (or not) of scientific ideas as based on processes in the mind-brain, and therefore being a subject for study, particularly by scientists and engineers studying models of the mind. A particular aspect of the DL models of the mind relevant to acceptance of scientific ideas explains what is conscious and what is unconscious in cognition. DL describes cognition as a process "from vague to crisp." The vague part of the DL process is unavailable to consciousness. Only the final results of these processes, the crisp, approximately logical states of the mind are available to consciousness. Similar ideas where suggested by Grossberg, who called "resonances" these states available to consciousness.[60] Experimental evidence discussed in the next section suggests that these conscious states make up only about 0.1% of the brain operations; the rest are illogical neuronal firings, etc., which are unconscious.

Our consciousness therefore is logically biased. What is illogical in the brain (99.9%) is unavailable, or barely available to conscious. What is conscious is also logical. Therefore all our intuitions are biased toward logic.

Theories that are based on logical laws are easily accepted by the community, even as logical (or nearly logical) operations make up only about 0.1% (or less) of the brain operations. Theories exploring laws of unconscious operations of the brain have to wait for decades, even so these make more than 99.9% of workings of the brain. This is the reason why outstanding mathematicians, such as Gilbert believed that logic can explain the mind: "The fundamental idea of my proof theory is none other than to describe the activity of our understanding, to make a protocol of the rules according to which our thinking actually proceeds."[61] This is why, even after Godel, logical AI made up a huge splash in the 1950s and 60s, and why logically based algorithms in engineering, logically-based explanations in psychology and cognitive science still attract a lot of followers. Whereas Aristotelian theory of the mind (emphasizing illogical forms) waited for 2500 years before it is now understood, theories of Einstein, Zadeh, Grossberg, and many others have to wait for decades to be accepted and recognized.

This understanding of the role of logic as a "spoiler" of scientific thinking might help accelerating scientific progress. Logic has to be used to explain results to others, to write papers. But logic does not help, when making scientific discoveries.

4.3 Experimental evidence for the DL mechanisms in the brain

Neural processes of perception and cognition involved in DL are complex and only recently understood[60,62,63]. Using this understanding, experimental validation of DL can be obtained by everyone in 3 seconds. Just close you eyes and imagine a familiar object that you observed in front of you just a second ago. Your imagination is vague-fuzzy, not as crisp as perception of the object with opened eyes. We know that imagination is produced in the visual cortex by top-down signals from models in your memory. This proves that in the initial stages of perception memories-models producing top-down signals are vague, as in DL. This is a unique property of DL, no other theory emphasizes the fundamental role of vagueness of initial top-down projections.

Detailed neurological and fMRI neuroimaging studies[64,65] confirmed that conscious perceptions are preceded by activation of cortex areas, where top-down signals originate; initial top-down projections are vague and unconscious. The DL equations were published and studied much earlier than their recent experimental confirmation; DL predicted vagueness of mental representations, before they are matched to sensory signals. These experiments confirmed the unique property of DL, a process "from vague to crisp."

In section 2 we discussed that DL maximizes knowledge and in this way models the mechanism of the knowledge instinct. According to Grossberg and Levine[66] theory of instincts and emotions there are specific emotions related to satisfaction or dissatisfaction of every instinct. In[12,20,23,46,47,50,51,51,51,52] we discussed that specific emotions associated with the knowledge instinct are aesthetic emotions, they serve as foundations of all our higher mental abilities. These references discuss the role of the beautiful in cognition and consciousness, and the role of music in evolution of cultures. Existence of these emotions was demonstrated experimentally in[67].

4.4 Future directions: "Ph.D. in 1 year, 30 topics"

This paper describes a new approach to several research areas, addressing a number of classical and emerging engineering problems. Every one can be a topic for a Ph.D. dissertation. Lead positions in government and industrial labs, tenured University positions, many sources of funding are available to young researchers in these areas. Learning situations, described in section 3, can be applied to many application problems in government, industrial, and financial areas. In addition to learning situations, as sets of objects, learning essential relations among objects should be demonstrated, as described in the last paragraph of section 3. Is the described technique directly applicable? What additional ideas are required? This should be demonstrated in several areas.

Object recognition is still an unsolved problem. Using the DL technique of section 3 an object can be modeled as a set of features and relations[68]. It is possible that relatively few features and relations specific to objects and events would be sufficient in many applications.

DL eqs.(2, 3) describe a single layer interaction of top-down and bottom-up signals. An approach to combining layers into a hierarchy have been discussed in[43,55]. It should be completed. Another direction is using simulations of agents to perform detailed studies of multi-layer hierarchical DL. A related direction will simulate multiple intelligent agents, each endowed with the DL brain-mind. These references also discuss how the DL agents can interact with a mechanism modeling human language. What changes are necessary for a self-expanding hierarchy? What is the optimal hierarchy? Would the highest models of meaning and purpose appear in a single-agent DL system, under the drive from KI? Or would it be necessary to consider multi-agent systems with communicating agents, competing for various resources, and using their knowledge and hierarchical organization in this competition, before importance of the highest models of meaning would be observed? What would be the differences between these models? What would we learn from such models about the meanings of our own lives? This research program encompasses an ambitious goal of modeling the mind, human societies, cultures, and their evolutions.

Future research will relate DL to chaotic neurodynamics[54,69]; this reference suggests that DL might be "implemented" in the brain as a phase transition from high-dimensional chaotic state to a low dimensional chaos. Research on spiking neurons[70] possibly implies that DL might be "implemented" in the brain as an increased correlation of spiking trains. Future research will relate our discussion of conscious and unconscious DL mechanisms to other research on consciousness[71,72].

A hypothesis in the previous section, suggesting that algorithms and scientific theories based on logic are accepted much faster than those that use logic to uncover illogical bases, should be verified in history of science and psychological experiments.

The knowledge instinct is not the only mechanism driving human decisions. The basis of the Tversky-Kahneman theory[59] is a different mechanism of decision-making, aimed at discarding "too much" knowledge; there is a well-established psychological principle of "effort minimization," including cognitive effort. It would be necessary to develop more complicated models, which will take into account both principles[73].

DL should be extended to modeling mind's ability for language, interactions between cognition and language, and role of emotions in languages. Initial results[36,37,43,42,43,48,53,54,55] indicate that these processes define evolution of languages and cultures. In many applications a fast progress can be achieved by simulating multi-agent systems, each agent possessing a DL mind. A fascinating research area is simulating intelligent agents with cognitive dissonances and music ability[47,50,51,50,51].

Recent experimental studies[67] confirmed existence of the knowledge instinct and aesthetic emotions related to knowledge. Using neuro-imaging studies these results should be related to specific mind's modules and circuits. Further experimental and theoretical studies should extend these results, as mentioned in the previous paragraph, to multiplicity of aesthetic emotions in language prosody, in music,[51] study geometry and topology of these emotional spaces, and relate them to emotions of cognitive dissonances.

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