# SEMIOTIC FUNDAMENTALS OF INFORMATION PROCESSING IN HUMAN BRAIN

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**ABSTRACT**

The paper discusses a mathematical nature of signs and symbols, and relates it to information processing and understanding, structure of the mind and brain, learning, and pattern recognition. I discuss past limitations of algorithms and neural networks, combina-torial complexity, the roles of concepts and emotions in mind's mechanisms, and various types of logic underlying mathematical techniques. A mathematical theory of semiosis, adaptive processes of sign interpretation, is described; it includes a similarity measure between signals and internal representations and fuzzy dynamic logic, a mechanism of the similarity maximization. Mathematical mechanisms of sign and symbol processing are presented and related to the functioning of mind.

**KEYWORDS:** *semiotics, symbols, fuzzy dynamic logic, neural networks, emotions, concepts, intelligent systems.*

## 1. SEMIOTICS, MIND, AND BRAIN

Semiotics studies signs and symbols, which are generally understood as entities designating some other entities in the world or in the mind. Using words like *mind, thought, imagination, emotion, concept* represents a specific challenge: people use these words in many ways colloquially, but their use in science and especially in mathematics of intelligence has not been uniquely defined and is a subject of active research and ongoing debates [1]. Whereas standardized definitions come at the end of the development of a theory (like "force" was defined by the 2nd Newton's law, following centuries of less precise usage) this paper adheres to a following guidance: we need to make sure that our definitions: (1) are mathematically exact, (2) correspond to the usage in scientific and mathematical community, (3) correspond to the general usage. According to a dictionary [2], mind includes conscious and unconscious processes, especially thought, perception, emotion, will, memory, and imagination, and it originates in brain. These constituent notions will be discussed throughout the paper. Specific neural mechanisms in brain "implementing" various mind functions constitute the relationship between the mind and brain; we will discuss how the mathematical descriptions of mind are implemented in brain.

In mathematics and in "Symbolic AI" there is no difference between signs and symbols. Both are considered as notations, arbitrary non-adaptive entities with axiomatically fixed meaning. But in general culture, symbols are understood also as psychological processes of sign interpretation. Jung emphasized that symbol-processes connect conscious and unconscious [3], Pribram wrote of symbols as adaptive, context-sensitive signals in the brain, whereas signs he identified with less adaptive and relatively context-insensitive neural signals [4].

In this paper I use "symbol" as a symbol-process, corresponding to general notions of symbol in culture and psychology. The symbol-processes are closely related to the processes of thinking, and a mathematical theory suitable for the description of sym-bols is closely related to the mathematical description of the working of the mind.

A broad range of opinions exists on the mathematical methods suitable for the description of the mind. Founders of artificial intelligence thought that formal logic was sufficient [5] and no specific mathematical techniques would be needed to describe the mind [6]. An opposite point of view is that there are few specific mathematical constructs, "the first principles" of mind. Among researchers taking this view is Grossberg, who suggests that the first principles include a resonant matching between lower-level signals [7] and higher-level representations and emotional evaluation of conceptual contents [8]; Zadeh develops theory of granularity [9], Meystel develops hierarchical multiscale organization with specific intra-level closed-loop structures [10]; and the author, suggests similarity measures between lower-level signals and higher-level representations [11] and the fuzzy dynamic logic [12] among first principles of mind.

## 2. MIND, LOGIC, AND COMPLEXITY

Understanding the meaning of signals coming from sensory organs involves associating the subsets of signals corresponding to an object with internal representations. This recognition activates internal brain signals leading to mental and behavioral responses involved in understanding.

Developing mathematical descriptions of the very first *recognition* step of this seemingly simple association-recognition-understanding process has not been easy, a number of difficulties have been encoun-tered during the past fifty years. These difficulties have been summarized under the term combinatorial complexity (CC) [11]. The problem was first identified in pattern recognition and classification problems in the 1960s and was named "the curse of dimensionality" [13]. The following thirty years of developing adaptive statistical pattern recognition and neural network algorithms led to a conclusion that these approaches often encountered *CC of learning requirements*. Rule-based systems were proposed to solve the problem of learning complexity. An initial idea was that rules would capture the required knowledge and eliminate a need for learning. However, rule systems and expert systems in the presence of variability, encountered *CC of rules*. Model-based systems were proposed to combine advantages of adaptivity and rules by utilizing adaptive models, but they encountered *computational CC* (N and NP complete algorithms).

Combinatorial complexity has been related to the type of logic, underlying various algorithms and neural networks [14]. Formal logic is based on the "law of excluded third", 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 combinatorial complexity. In fact, combinatorial complexity of algorithms based on logic has been related to the Gödel theory: it is a manifestation of the incompleteness of logic in finite systems [15]. Multivalued logic and fuzzy logic were proposed to overcome limitations related to the law of excluded third [16]. Yet the mathematics of multivalued logic is no different in principle from formal logic. 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 might become similar to formal logic.

Another view on these difficulties can be obtained by comparing mathematical techniques to human mind. An essential role of emotions in the working of the mind was analyzed from the psychological and neural perspective by Grossberg [17], from the neurophysiological perspective by Damazio [18], and from the learning and control perspective by the author [19]. One reason for engineering community being slow in adopting these results is the cultural bias against emotions as a part of thinking processes. Plato and Aristotle thought that emotions are "bad" for intelligence, this is a part of our cultural heritage, and the founders of Artificial Intelligence repeated it. Yet, as discussed in the next section, combining conceptual understanding with emotional evaluations might be crucial for overcoming the combinatorial complexity as well as the related difficulties of logic.

## 3. MODELING FIELD THEORY (MFT)

Modeling field theory [11], summarized below, associates lower-level signals with higher-level representations, resulting in understanding of signals, while overcoming the difficulties described in the previous section. It is achieved by using flexible measures of similarity between the representations and the input signals combined with the fuzzy dynamic logic. Modeling field theory is a multi-level, hetero-hierarchical system. This section describes a basic mechanism of interaction between two adjacent hierarchical levels of signals (fields of neural activation); sometimes, it will be more convenient to talk about these two signal-levels as an input to and output from a (single) processing-level.

At each level, the output are concepts recognized (or formed) in input signals. Input signals **X** are associated with (or recognized, or grouped into) concepts according to the representations-models and similarity measures at this level. In the process of association-recognition, models are adapted for better representation of the input signals; and similarity measures are adapted so that their fuzziness is matched to the model uncertainty. The initial uncertainty of models is high and so is the fuzziness of the similarity measure; in the process of learning models become more accurate and the similarity measure more crisp, the value of the similarity increases. We call this mechanism fuzzy dynamic logic.

### 3.1 Internal Models, Learning, and Similarity

During the learning process, new associations of input signals are formed resulting in evolution of new concepts. Input signals $\{\mathbf{X}(n),\ n \in N\}$, is a field of input neuronal synapse activation levels, $\mathbf{X} = \{X_d,\ d = 1,\ldots D\}$; a set of concepts $\{h \in H\}$ is characterized by internal parameters $\{\mathbf{S}_h\}$ and by models (representations) of the signals $\{\mathbf{M}_h(\mathbf{S}_h,n)\}$ corresponding to concepts $\{h\}$. For each model h, the set of parameters is denoted as $\mathbf{S}_h = \{S^a_h,\ a = 1,\ldots A\}$. Learning process increases a similarity measure between the sets of models and signals, $L(\{\mathbf{X}\},\{\mathbf{M}\})$. The similarity measure is a function of model parameters and associations between the input synapses and concepts-models. A similarity measure is designed so that it treats each model as an alternative for each subset of signals

$$L(\{\mathbf{X}\},\{\mathbf{M}\}) = \prod_{n\in N} \sum_{h\in H} r(h)\, l(\mathbf{X}(n) \mid h), \quad (1)$$

here $l(\mathbf{X}(n)|h)$ (or simply $l(n|h)$) is a conditional partial similarity between signal vector $\mathbf{X}(n)$ and model $\mathbf{M}_h$ (when mapping this terminology onto its implemetation in the brain, n and h are neural indexes numbering individual neurons or small groups of neurons). For example, $l(n|h)$ can be selected as a probability density function. Then L is a total likelihood (this interpretation does not require statistical independence among signal vectors n and n': dependencies are accounted for by model dependencies on {n}).

In the process of learning, concept-models are constantly modified. From time to time a system forms a new concept, while retaining an old one as well; alternatively, old concepts are sometimes merged. Formation of new concepts and merging of old ones require a modification of the similarity measure (1); the reason is that more models always result in a better fit between the models and data. This is a well known problem, it can be addressed by reducing (1) using a "penalty function", p(N,M) that grows with the number of models M, and this growth is steeper for a smaller amount of data N. For example, an asymptotically unbiased maximum likelihood estimation leads to multiplicative $p(N,M) = \exp(-N_{par}/2)$, where $N_{par}$ is a total number of adaptive parameters in all models (this penalty function is known as Akaike Information Criterion, see [11] for further discussion and references).

In case, when a set of observations, N, corresponds to a continuous flow of signals, for example, a flow of visual stimuli in time and space, it is convenient instead of eq.(1) to consider its continuous version,

$$L = \exp ?_{N} \ln \Big(\sum_{h \in H} r(h)\, l(\mathbf{X}(n) \mid h) \Big), \qquad (2)$$

where N is a continuum, such as time-space. In this case, models describe continuous modeling fields and maximization of similarity L can be compared to minimization of action in a physical field theory.

### 3.2 Fuzzy dynamic logic and MFT

The learning process consists in estimating internal parameters **S** and associating subsets of signals with concepts by maximizing the similarity (1). When likelihood is used as a similarity measure, this is a problem of the maximum likelihood estimation. Note, that (1) contains a total of $H^N$ items; this is a source of the combinatorial complexity in many algorithms (called maximum hypothesis testing) which attempt to maximize similar expressions by first maximizing each item over the parameters and then finding the maximal item.

Modeling field theory solves this problem by utilizing fuzzy dynamic logic [11,20]. Let us introduce association variables f(h|n)

$$f(h|n) = r(h)\, l(\mathbf{X}(n)|h) \Big/ \sum_{h' \in H} r(h')\, l(\mathbf{X}(n)|h'). \quad (3)$$

Eq.(3) looks like the Bayes formula for a posteriori probabilities, if l(n|h) are conditional likelihoods. An internal dynamics of the Modeling Fields (MF) is defined as follows,

$$df(h \mid n)/dt = f(h \mid n) \sum_{h' \in H} \{[\delta_{hh'} - f(h'|n)] \cdot$$

$$[?\ln l\,(n|h')/?\mathbf{M}_{h'}]\, \partial \mathbf{M}'_{h'}/\partial \mathbf{S}_{h'} \cdot d\mathbf{S}_{h'}/dt, \qquad (4)$$

$$d\mathbf{S}_h/dt=\{?_{N} f(h|n)[?\ln l(n|h)/?\mathbf{M}_h]\partial \mathbf{M}'_h/\partial \mathbf{S}_h, \quad (5)$$

here

$\delta_{hh'}$ is 1 if h=h', 0 otherwise. (6)

Parameter t is the time of the internal dynamics of the MF system (like a number of internal iterations). A more specific form of (5) can be written when Gaussian-shape functions are used for conditional partial similarities,

$$l(n|h) = G(\mathbf{X}(n) \mid \mathbf{M}_h(\mathbf{S}_h, n), \mathbf{C}_h). \qquad (7)$$

where G is a Gaussian function with mean $\mathbf{M}_h$ and covariance matrix $\mathbf{C}_h$ (this is not a necessary assumption, but it will simplify some discussions later, also, it is not same as usual Gaussian limitation, in fact, it is not much of a limitation at all, because a weighted sum of Gaussians in (1) can approximate any positive function). And let us specify the dynamics of the MFT as follows,

$$dS^{a}_{h}/dt \;=\; [Y_{h}]^{-1\,ab}\, Z_{h}^{b}\,, \tag{8}$$

$$d\mathbf{C}_{h}/dt = -0.5\mathbf{C}_{h}^{-2}\; ?_{N}\, f(h|n)[\mathbf{C}_{h}\text{-}\mathbf{D}_{nh}\,\mathbf{D}_{nh}^{T}]; \tag{9}$$

$$\mathbf{D}_{nh} \;=\; (\,\mathbf{X}(n) - \mathbf{M}_{h'}\,)\,, \tag{10}$$

$$Y_{h}^{ab} \;=\; ?_{N}\, f(h|n)[\mathbf{M}^{;a}_{h}\mathbf{C}_{h}^{-1}\mathbf{M}^{;b}_{h}], \tag{11}$$

$$Z_{h}^{b} \;=\; ?_{N}\, f(h|n)[\mathbf{M}^{;b}_{h}\mathbf{C}_{h}^{-1}\mathbf{D}_{nh}], \tag{12}$$

here superscript T denotes a transposed row-vector; summation is assumed over repeated indexes a, b; and (;) denotes partial derivatives with respect to parameters S with corresponding indexes:

$$\mathbf{M}^{;b}_{h} \;=\; \partial\mathbf{M}_{h} \,/\, \partial S^{b}_{h}\,. \tag{13}$$

The following theorem was proven.

*Theorem*. Equations (3) through (6) (or (3) and (8 through 12)) define a convergent dynamic system MF with stationary states defined by $\max_{\{\mathbf{S}_h\}} L$.

It follows that the stationary states of an MF system give the maximum similarity solution of the model-based pattern recognition problem. When likelihood is used as similarity, the stationary values of parameters $\{\mathbf{S}_h\}$ are asymptotically unbiased and efficient estimates of these parameters [21]. A computational complexity of the MF method is linear in N.

### 3.3 MFT hierarchical organization

The previous sub-section described a single processing layer in a hierarchical MFT system. An input to each layer is a set of signals $\mathbf{X}(n)$, or in neural terminology, an input field of neuronal activations. An output are the activated models $\mathbf{M}_h(\mathbf{S}_h, n)$; it is a set of models or concepts recognized in the input signals. Equations (3-6) or (3) and (7-12) describe a loop-process: at each iteration (or internal-time t) the l.h.s. of the equations contain association variables f(h|n) and other model parameters computed at the previous iteration. In other words, the output models “act” upon the input to produce a “refined” output models (at the next iteration). This process is directed at increasing the similarity between the models and signals. It can be described as an internal behavior generated by the models.

The output models initiate other actions as well. First, activated models (neuronal axons) serve as input signals to the next processing layer, where more general concept-models are recognized or created (internal behavior within the MFT system). Second, concept-models along with the corresponding instinctual signals and emotions may activate behavioral models and generate behavior directed into the outside world (a process not contained within the above equations).

MFT describes an intelligent system composed of multiple adaptive intelligent agents: each concept-model is an agent, which is "dormant" until activated by a high similarity value. When activated, it is adapted to the signals, so that the similarity increases. Every piece of signal may activate several concepts, which "compete" with each other, while adapting to the new signals.

### 3.4 MFT theory of mind

*MFT dynamics*, (3) and (4-6) or (7-12), describes an elementary process of perception or cognition, in which a large number of model-concepts compete for incoming signals, model-concepts are modified and new ones are formed, and eventually, connections are established among signal subsets on the one hand, and model-concepts on the other. Perception refers to processes in which the input signals come from sensory organs and model-concepts correspond to objects in the surrounding world. Cognition refers to higher levels in the hierarchy where the input signals are concepts activated at lower levels and model-concepts are more complex and correspond to situations and relationships among lower-level concepts.

A salient mathematical property of this processes ensuring a smooth convergence is a correspondence between uncertainty in models (that is, in the knowledge of model parameters) and uncertainty in associations f(h|n). In perception, as long as model parameters do not correspond to actual objects, there is no match between models and signals; many models poorly match many objects, and associations remain fuzzy; this can be described more specifically, if Gaussian functions are used for $l(\mathbf{X}|h)$: for poorly matched models, the covariances, $\mathbf{C}_h$, are large (that is, model uncertainties are large), which in turn prevents f(h|n) from attaining definite (0,1) values. Eventually, one model (h') wins a competition for a subset {n'} of input signals $\mathbf{X}(n)$, when parameter values match object properties, $\mathbf{C}_{h'}$ becomes smaller than other $\mathbf{C}_h$, and f(h'|n) values become close to 1 for $n \in \{n'\}$ and 0 for $n \notin \{n'\}$. Upon the convergence, the entire set of input signals {n} is divided into subsets, each associated with one model-object, $\mathbf{C}_h$ become small, and fuzzy a priori concepts become crisp concepts. Cognition is different from perception in that models are more general, more abstracts, and input signals are the activation signals from concepts identified (cognized) at a lower hierarchical level; the general mathematical laws of cognition and perception are similar in MFT. Let us discuss relationships between the MFT theory, theory of solitons in non-linear systems and concepts of mind originated in psychology, philosophy, linguistics, aesthetics, neuro-physiology, neural networks, artificial intelligence, pattern recognition, and intelligent systems.

*Solitons and MFT resonances*. The physical nature of concepts of mind in MFT is similar to that of solitons. If the data $\mathbf{X}(n)$ are all given from the very beginning, equations (3-6) or (7-12) converge to a fixed point of MFT system. This fixed point is comprised of a number of resonances [22] between the field of models and field of data, in other words, the models come into a resonance with the data, and the system stays in this resonant state. Formation of a resonance takes different time (number of iterations) for various models, and it is more proper to talk about each model coming into a resonance with a corresponding data subset. If there is a continuous flow of data, $\mathbf{X}(n,t)$, a resonance is a long-living state (long comparative to a single iteration cycle). The nature of this resonance between the modeling fields and the data field is such that a particular subset of data (corresponding to an object h) "drives" the modeling-field to a specific value (or pattern) $\mathbf{M}_h(\mathbf{S}_h,n,t)$, and these modeling-field values "drive" the association-fields, f(h|n), to {0,1} values. It follows that concepts of mind in MFT theory are resonant states, or solitons of a highly nonlinear MFT system. It is interesting to note recent results [23] establishing relationships between solitons in certain nonlinear systems and theorems of inversive geometry. More research is needed to establish general relationships between concepts of mind as long-living resonant states in a nonlinear system and a body of results obtained in the theory of integrable systems and solitons [24].

*Elementary thought-process, consciousness, and unconscious*. A thought-process or thinking involves a number of sub-processes and attributes, including internal representations and their manipulation, attention, memory, concept formation, knowledge, generalization, recognition, understanding, meaning, prediction, imagination, intuition, emotion, decisions, reasonining, goals, behavior, conscious and unconscious [7,10,11].

A "minimal" subset of these processes has to involve mechanisms for afferent and efferent signals [22], in other words, bottom-up and top-down signals coming from outside (external sensor signals) and from inside (internal representation signals). According to Carpenter and Grossberg [22] every recognition and concept formation process involves a "resonance" between these two types of signals. In MFT, at every level in a hierarchy the afferent signals are represented by the input signal field **X**, and the efferent signals are represented by the modeling field signals $\mathbf{M}_h$; resonances correspond to high similarity measures l(n|h) for some subsets of {n} that are "recognized" as concepts (or objects) h. The mechanism leading to the resonances is given by (3-6) or (7-12), and we call it an elementary thought-process. The elementary thought-process involves elements of conscious and unconscious processes, imagination, memory, internal representations, concepts, instincts, emotions, understanding and behavior as further described later.

A description of working of the mind as given by the MFT dynamics was first provided by Aristotle [25], describing thinking as a learning process in which an a priori form-as-potentiality (fuzzy model) meets matter (sensory signals) and becomes a form-as-actuality (a concept). Jung suggested that conscious concepts are developed by mind based on genetically inherited structures of mind, archetypes, which are inaccessible to consciousness [3]; and Grossberg [7] suggested that only signals and models attaining a resonant state (that is signals matching models) reach consciousness.

*Understanding*. In the elementary thought process, subsets in the incoming signals are associated with recognized model-objects, creating *phenomena* (of the MFT-mind) which are *understood* as objects, in other words *signal subsets* acquire *meaning* (e.g., a subset of retinal signals acquires a meaning of a chair). There are several aspects to understanding and meaning. First, object-models are connected (by emotional signals [8,11,19]) to instincts that they might satisfy, and also to behavioral models that can make use of them for instinct satisfaction. Second, an object is understood in the context of a more general situation in the next layer consisting of more general concept-models, which accepts as input-signals the results of object recognition. That is, each recognized object-model (phenomenon) sends (in neural terminology, activates) an output signal; and a set of these signals comprises input signals for the next layer models, which 'cognize' more general concept-models. And this process continues up and up the hierarchy of models and mind toward the most general models a system could come up with, such as models of universe (scientific theories), models of self (psychological concepts), models of meaning of existence (philosophical concepts), models of a priori transcendent intelligent subject (theological concepts).

*Imagination*. Imagination involves excitation of a neural pattern in a visual cortex in absense of an actual sensory stimulation (say, with closed eyes) [7]. Imagination was often considered to be a part of thinking processes; Kant [26] emphasized the role of imagination in the thought process, he called thinking "a play of cognitive functions of imagination and understanding". Whereas pattern recognition and artificial intelligence algorithms of recent past would not know how to relate to this [5,6], Carpenter and Grossberg resonance model [22] and the MFT dynamics both describe imagination as an inseparable part of thinking: imagined patterns are top-down signals that *prime* the percepting cortex areas (*priming* is a neural terminology for making neural cells to be more readily excited). In MFT, the imagined neural patterns are given by models $\mathbf{M}_h$. MFT (in agreement with neural data) just adds details to Kantian description: thinking is a play of *higher-hierarchical-level* imagination and *lower-level* understanding. Kant identified this "play" [described by (3-6) or (7-12)] as a source of aesthetic emotion; modeling aesthetic emotion in MFT is described later.

*Mind vs. Brain.* Historically, the mind is described in psychological and philosophical terms, whereas the brain is described in terms of neurobiology and medicine. Withing scientific exploration the mind and brain are different description levels of the same system. Establishing relationships between these description is of great scientific interest. Today we approach solutions to this challenge [27], which eluded Newton in his attempt to establish physics of "spiritual substance" [28]. General neural mechanisms of the elementary thought process (which are similar in MFT and ART [22]) have been confirmed by neural and psychological experiments, this includes neural mechanisms for bottom-up (sensory) signals, top-down "imagination" model-signals, and the resonant matching between the two [29]. Adaptive modeling abilities are well studied with adaptive parameters identified with synaptic connections [30]; instinctual learning mechanisms have been studied in psychology and linguistics [31].

*Instincts and emotions*. Functioning of the mind and brain cannot be understood in isolation from the system's "bodily needs". For example, a biological system (and any autonomous system) needs to replenish its energy resources (eat); this and other fundamental unconditional needs are indicated to the system by instincts, which could be described as internal sensors. Emotional signals, generated by this instinct are perceived by consciousness as "hunger", and they activate behavioral models related to food searching and eating. In this paper we are concerned primarily with the behavior of recognition: instinctual influence on recognition modify the object-perception process (3) - (6) in such a way, that desired objects "get" enhanced recognition; it can be accomplished by modifying priors, r(h).

*Aesthetic emotions and instinct for knowledge*. Recognizing objects in the environment and understanding their meaning is so important for human evolutionary success that there has evolved an instinct for learning and improving concept-models. This instinct is described in MFT by maximization of similarity between the models and the world, (1). Emotions related to satisfaction-dissatisfaction of this instinct are perceived by us as harmony-disharmony (between our understanding of how things ought to be and how they actually are in the surrounding world). According to Kant [32] these are aesthetic emotions.

*Intuition* includes an intuitive perception (imagination) of object-models and their relationships with objects in the world, as well as higher-level models of relationships among simpler models. Intuition involves fuzzy unconscious concept-models, which are in a state of being learned and being adapted toward crisp and conscious models (a theory); such models may satisfy or dissatisfy the knowledge instinct in varying degrees before they are accessible to consciousness, hence the complex emotional feel of an intuition. The beauty of a physical theory discussed often by physicists is related to satisfying our feeling of purpose in the world, that is, satisfying our need to improve the models of the meaning in our understanding of the universe.

*Beauty*. Harmony is an elementary aesthetic emotion related to improvement of object-models. Higher aesthetic emotions are related to the development of more complex "higher" models: we perceive an object or situation as aesthetically pleasing if it satisfies our learning instinct, that is the need for improving the models and increasing similarity (1). The highest forms of aesthetic emotion are related to the most general and most important models. According to Kantian analysis [32], among the highest models are models of the meaning of our existence, of our purposiveness or intentionality, and beauty is related to improving these models: we perceive an object or a situation as beautiful, when it stimulates improvement of these highest models of meaning. Beautiful is what “reminds” us of our purposiveness.

*Theory testing and future directions.* The general neural mechanisms of the elementary thought process, which includes neural mechanisms for bottom-up (sensory) signals, top-down “imagination” model-signals, and the resonant matching between the two [33], have been confirmed by neural and psychological experiments (these mechanisms are similar in MFT and ART [22]). Adaptive modeling abilities are well studied and adaptive parameters have been identified with synaptic connections [34]; instinctual learning mechanisms have been studied in psychology and linguistics [35]. Ongoing and future research will confirm, disprove, or suggest modifications to specific mechanisms of model parameterization and parameter adaptation (5) or (8), reduction of fuzziness during learning (9), similarity measure (1) as a foundation of aesthetic instinct for knowledge, relationships between psychological and neural mechanisms of learning on the one hand and, on the other, aesthetic feelings of harmony and emotion of beautiful. Differentiated forms of (1) need to be developed for various forms of the knowledge instinct (child development, language learning, etc.) Future experimental research needs to study in details the nature of hierarchical interactions: to what extent the hierarchy is “hardwired” vs. adaptively emerging; what is a hierarchy of learning instinct? theory of emerging hierarchical models will have to be developed (that is, adaptive, dynamic, fuzzy hierarchy- heterarchy).

## 4. THINKING PROCESS AND SEMIOTICS

Semiotics studies symbol-content of culture [36]. For example, consider a written word "chair". It can be interpreted by a mind to refer to something else: an entity in the world, a specific chair, or the concept "chair" in the mind. In this process, the mind, or an intelligent system is called *an interpreter*, the written word is called *a sign*, the real-world chair is called *a designatum*, and the concept in the interpreter's mind, the internal representation of the results of interpretation is called *an interpretant* of the sign. The essence of a sign is that it can be interpreted by an interpreter to refer to something else, a designatum. This process of sign interpretation is an element of a more general process called semiosis which consists of multiple processes of sign interpretation at multiple levels of the mind hierarchy.

In classical semiotics [37] words *sign* and *symbol* were not used consistently; in this paper, a sign means something that can be interpreted to mean something else (like a mathematical notation, or a word), and the process of interpretation is called a symbol-process, or symbol. Intepretation, or understanding of a sign by the mind according to MFT is due to the fact that a sign (e.g., a word) is a part of an object-model (or a situation-model at higher levels of the mind hierarchy). The mechanism of a sign interpretation therefore involves first an activation of an object-model, which is connected to instincts that the object might satisfy, and also to behavioral models that can make use of this object for instinct satisfaction. Second, a sign is understood in the context of a more general situation in the next layer consisting of more general concept-models, which accepts as input-signals the results of lower-level sign recognition. That is, recognized signs comprise input signals for the next layer models, which ‘cognize’ more general concept-models.

A symbol-process of a sign interpretation coincides with an elementary thought-process. Each sign-interpretation or elementary thought process, a symbol, involves conscious and unconscious, emotions and concepts; this definition connecting symbols to archetypes (fuzzy unconscious model-concepts) corresponds to a usage in general culture and psychology [3,4]. As described previously, this process continues up and up the hierarchy of models and mind toward the most general models. In semiotics this process is called *semiosis*, a continuous process of creating and interpreting the world outside (and inside our mind) as an infinite hierarchical stream of signs and symbol-processes.

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