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Mirror neurons, language, and embodied cognition

Leonid I. Perlovsky [b,a,*], Roman Ilin [b]

[a] *Harvard University, United States*
[b] *AFRL, United States*

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ABSTRACT

Basic mechanisms of the mind, cognition, language, its semantic and emotional mechanisms are modeled using dynamic logic (DL). This cognitively and mathematically motivated model leads to a dual-model hypothesis of language and cognition. The paper emphasizes that abstract cognition cannot evolve without language. The developed model is consistent with a joint emergence of language and cognition from a mirror neuron system. The dual language–cognition model leads to the dual mental hierarchy. The nature of cognition embodiment in the hierarchy is analyzed. Future theoretical and experimental research is discussed.

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1. Basic mechanisms of the mind

This paper develops a hypothesis about the role of language in cognition. Language is not only a communication device but also a fundamental part of cognition and learning concepts, especially abstract concepts. The mind abilities for perception and cognition involve interactions of bottom-up and top-down signals (Grossberg, 1982; Kosslyn, 1980, 1994; Schacter & Addis, 2007). A fundamental property of this interaction is a process "from vague to crisp". Vague, distributed, and unconscious mental representations evolve into crisp and conscious perceptions and cognitions; development in this paper is based on previous theoretical, simulation, and experimental results (Bar, 2007; Bar et al., 2006; Perlovsky, 1987, 1988a, 1994, 1997a, 2001, 2002a, 2006a; Perlovsky & McManus, 1991). The process "from vague to crisp" is modeled mathematically by neural modeling fields and dynamic logic (DL), mathematical models describing evolution from vague mental states (perception representations, plans, concepts, actions) to crisp ones, and the adequacy of this model for actual brain–mind processes has been confirmed in brain imaging experiments (Bar, 2007; Bar et al., 2006; Perlovsky, 2009c).

NMF is a neural architecture modeling the mind (Perlovsky, 1987, 2001, 2006a). Its learning dynamics is described by DL, which overcomes combinatorial complexity (CC) encountered for decades by computational attempts to model brain–mind mechanisms (Kovalerchuk, Perlovsky, & Wheeler, 2011; Perlovsky, 1998, 2010d). The problem of CC was first identified in pattern recognition and classification research in the 1960s, and was named "the curse of dimensionality" (Bellman, 1961); high-dimensional pattern recognition systems required combinatorially large number of training examples. This difficulty has been attempted to overcome using rule systems (Minsky, 1975; Winston, 1984); rule systems work well when all aspects of the problem can be predetermined. However, in the presence of variability, the number of rules grew; rules became contingent on other rules and combinations of rules had to be considered; CC of rules has been encountered. Initial approaches to mathematical modeling of language also used rule systems and encountered similar problems (Chomsky, 1972).

Subsequent developments resulted in understanding that a fundamental mathematical reason for CC was its relation to logic used by computational approaches to modeling the mind (Perlovsky, 1996, 2001, 2012a). Even approaches specifically designed to overcome limitations of logic, such as fuzzy logic and neural networks, used logic at some algorithmic steps (e.g. for learning: 'this is a chair' is a logical statement). In addition, overcoming limitations of logic has been difficult psychologically, because, as demonstrated in the above references, vague parts of the DL process are inaccessible to consciousness. Only final states of the DL processes are accessible to consciousness, and these are approximately logical perceptions and cognitions. This have been proven experimentally (Bar, 2007; Bar et al., 2006; Perlovsky, 2006b, 2007a, 2007b, 2007f). Therefore subjective consciousness is biased toward logic. For thousands of years the mind has been considered as a logical system.

DL processes are mathematically equivalent to the knowledge instinct (KI), an inborn drive to maximize similarity between top-down and bottom-up signals (Perlovsky, 2001, 2006a; Perlovsky & McManus, 1991). The idea of KI is somewhat similar to the need for cognition (Cacioppo & Petty, 1982; Cacioppo, Petty, Feinstein, & Jarvis, 1996) and to reinforcement learning (Sutton & Barto, 1998),

* Corresponding author at: AFRL, United States.
E-mail addresses: leonid.perlovsky@hanscom.af.mil, leonid@seas.harvard.edu (L.I. Perlovsky).

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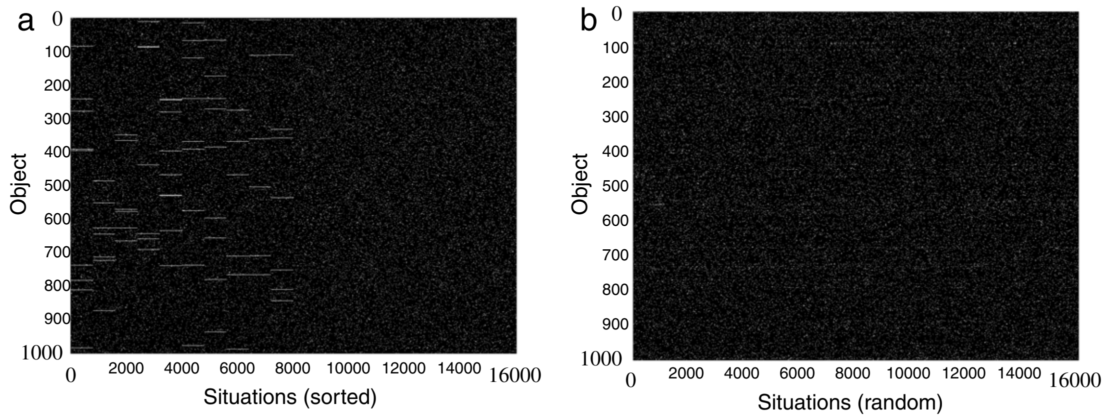

Fig. 1. Learning situations; white dots show present objects and black dots correspond to absent objects. Vertical axes show 1000 objects, and horizontal axes show 10 situations each containing 10 relevant objects and 40 ransom one; in addition, there 5000 "clutter" situations containing only random objects. Fig. 1(a) shows situations sorted along the horizontal axis; hence there are horizontal lines corresponding to relevant objects (the right half contains only random noise). Fig. 1(b) show the same situations in random order, which looks like random noise.

with maximization of knowledge being the reinforcer. Instincts or inborn drives are understood and modeled in this paper according to the Grossberg–Levine theory of drives and emotions (1987): instincts can be modeled as internal sensors measuring vital bodily parameters; satisfaction and dissatisfaction of instinctual drives are experienced as emotions. According to Perlovsky (1988a, 2001, 2006a) and Perlovsky and McManus (1991), knowledge acquisition in the process of matching top-down and bottom-up signals is driven by KI. As with other instincts, there are specific emotions related to KI; these emotions related to knowledge since Kant (1790) are called aesthetic emotions (Perlovsky, 2001, 2002a, 2002b, 2006a). Experimental existence of these emotions has been demonstrated in Perlovsky, Bonniot-Cabanac, and Cabanac (2010). These emotions are inseparable from every process of perception and cognition. They are below the level of consciousness at lower levels of mental hierarchy (this hierarchy is approximate; see Carpenter & Grossberg, 1989). Near the top of the hierarchy they are associated with improving mental representations unifying the entire life experience and are perceived as emotions of the beautiful (Perlovsky, 2001, 2002b, 2006a, 2007c, 2007g, 2008a, 2010b).

A mathematical model of KI is maximization of a similarity between top-down and bottom-up signals,

$$L = \prod_{h \in H} \prod_{n \in N} \sum_{m \in M} r(m, h)\, l\,(n|m, h). \tag{1}$$

Here, h, n, m are indexes enumerating levels of the hierarchy, n and m enumerate bottom-up and top-down signals at level h, and $l\,(n|m, h)$ is a conditional similarity between signals n and m at level h; it is conditional on signal n originating from representation-model m (Perlovsky & Kozma, 2007). Similarity at every level h accounts for all combinations of signals n coming from any model m. Hence even at a single level there is a huge number of items M^N in Eq. (1); this is a basic reason for CC of most algorithms (Yardley, Perlovsky, & Bar, 2012).

The knowledge instinct maximizes similarity L over parameters of representations S. DL maximizes similarity L without CC. The DL process at every level h is given by

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

$$dS_m/dt = \prod_{n \in N} f(m|n)[\partial \ln l\,(n|m)/\partial M_m]\partial M_m/\partial S_m. \tag{3}$$

Values $f(m|n)$ associate bottom-up and top-down signals (n and m). In the DL process of learning these quantities evolve from vague and uncertain to crisp and certain (near 1 or 0). As demonstrated in Perlovsky (1988b, 1989, 1997a, 1997b), at certain conditions DL learns maximum information from available data.

2. Cognition example

At each level of the hierarchy, bottom-up signals interact with top-down signals. For concreteness, we consider the level of the situations: learning situations composed of objects. In a real brain–mind process, learning and recognition of situations proceeds in parallel with perception of objects, as well as lower-level and higher-level representations. To simplify the presentation, here we consider objects being already recognized. Situations are collections of objects; every situation thus is a collection of bottom-up signals corresponding to objects. The fundamental difficulty of learning and recognizing situations (as well as every higher-level representation) is that, when looking in any direction, a large number of objects is perceived. Some combinations of objects form "situations" important for learning and recognition, but most combinations of objects are just random collections, which the human mind learns to ignore. The total number of combinations exceeds by far the number of objects in the Universe. This is the reason for this problem having not being solved over the decades.

Following (Ilin & Perlovsky, 2010; Perlovsky & Ilin, 2010a, 2010b), we define conditional similarities as

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

Here, n is the index of bottom-up signals available for learning (say, a number of observed situations), I_o is the number of components of bottom-up signals (say the number of bottom-up signal objects in signal n), $\mathbf{X}(n) = (x_{n1}, \ldots, x_{ni}, \ldots, x_{nIo})$; and in the model representation $p_m = (p_{m1}, \ldots, p_{mi}, \ldots, p_{mIo})$, p_{mi} is the probability of component i being part of model representation m. In reality, bottom-up signals do not contain the same number of components, and Io varies with n, but here we ignore this for simplicity of notations.

We consider an example of learning higher-level representations (say, situations) from lower-level representations (say, objects). This example is considered in detail in Perlovsky (2010b) and Perlovsky and Ilin (2010a); Figs. 1 and 2 summarize the results. The data available for learning and recognition of situations in this example are illustrated in Fig. 1. Horizontal axes correspond to situations. Each situation is characterized by objects shown along

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