Abstract Intelligence:
Embodying and Enabling Cognitive Systems by Mathematical Engineering

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ABSTRACT

Basic studies in denotational mathematics and mathematical engineering have led to the theory of abstract intelligence (aI), which is a set of mathematical models of natural and computational intelligence in cognitive informatics (CI) and cognitive computing (CC). Abstract intelligence triggers the recent breakthroughs in cognitive systems such as cognitive computers, cognitive robots, cognitive neural networks, and cognitive learning. This paper reports a set of position statements presented in the plenary panel (Part II) of IEEE ICCI*CC'16 on Cognitive Informatics and Cognitive Computing at Stanford University. The summary is contributed by invited panelists who are part of the world's renowned scholars in the transdisciplinary field of CI and CC.

KEYWORDS

Abstract Intelligence, Applications, Artificial Intelligence, Brain-Inspired Systems, Cognitive Computers, Cognitive Engineering, Cognitive Informatics, Cognitive Robotics, Cognitive Systems, Computational Intelligence, Denotational Mathematics, Mathematical Engineering

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1. INTRODUCTION

Cognitive Informatics (CI) is a transdisciplinary enquiry of the internal information processing mechanisms and processes of the brain and abstract intelligence, as well as their applications in cognitive computing and cognitive engineering (Wang, 2002, 2003, 2006, 2007a; Wang et al., 2002, 2009b, 2010). CI is a contemporary field spanning across computer science, information science, cognitive science, brain science, neuroscience, intelligence science, knowledge science, robotics, cognitive linguistics, cognitive philosophy, and cognitive engineering. *Cognitive Computing* (CC) is a novel paradigm of intelligent computing platforms of cognitive methodologies and systems based on CI, which embodying computational intelligence by cognitive and autonomous systems mimicking the mechanisms of the brain (Wang, 2011b, 2012e, 2015b, 2016a; Wang et al., 2006). IEEE ICCI*CC'16 on Cognitive Informatics and Cognitive Computing has been held at Stanford University during Aug. 22-23, 2016. The theme of ICCI*CC'16 was on cognitive computing, big data cognition, and machine learning (Widrow, 2016; Zadeh, 2016; Wang et al., 2016b).

CI and CC emerged from transdisciplinary studies in both natural intelligence in cognitive/brain sciences (Anderson, 1983; Sternberg, 1998; Reisberg, 2001; Wilson & Keil, 2001; Wang, 2002, 2007a; Wang et al., 2002, 2008, 2009, 2016) and artificial intelligence in computer science (Bender, 1996; Poole et al., 1997; Zadeh, 1999; Widrow et al., 2015; Wang, 2010a, 2016c). Towards formal explanation of the structures and functions of the brain, as well as their intricate relations and interactions, formal models are sought for revealing the principles and mechanisms of the brain. This leads to the theory of abstract intelligence (αI) that investigates into the brain via not only inductive syntheses of theories and principles of intelligence science through mathematical engineering, but also deductive analyses of architectural and behavioral instances of natural and artificial intelligent systems through cognitive engineering. The key methodology suitable for dealing with the nature of αI is mathematical engineering (ME), which is an emerging discipline of contemporary engineering that studies the formal structural models and functions of complex abstract and mental objects and their systematic and rigorous manipulations (Wang, 2015a).

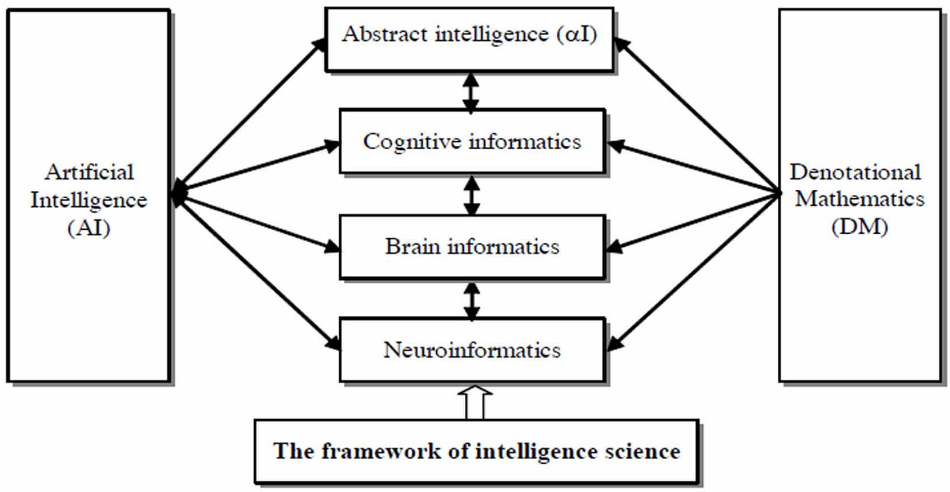
This paper is a summary of the position statements of invited panellists presented in the *Plenary Panel on Perspectives on Cognitive Computing, Big Data Cognition, and Machine Learning* (Part II), which was held in IEEE ICCI*CC 2016 (Wang et al., 2016b/c) at Stanford University, USA, on Aug. 23, 2016. It is noteworthy that the individual statements and opinions included in this paper may not necessarily be shared by all panellists.

2. THE THEORETICAL FRAMEWORK OF BRAIN AND INTELLIGENCE SCIENCES

The theoretical framework of brain science and intelligence science can be described as shown in Figure 1 according to CI studies (Wang, 2007a, 2008, 2009a, 2011b, 2012c/e, 2015b/d, 2016a). It it recognized that the brain may be explained by a hierarchically reductive structure at the logical, cognitive, physiological, and neurological levels from the bottom up, which form the studies known as abstract intelligence, cognitive informatics, brain informatics, and neuroinformatics. The synergy of multidisciplinary studies at all levels leads to the theory of CI for explaining the brain. The fundamental theories underpinning the framework of brain and intelligence sciences are abstract intelligence (Wang, 2009a, 2012c, 2015a) and denotational mathematics (Wang, 2008, 2009c, 2012a/b/d, 2015a).

- **Neuroinformatics (NI):** NI is the fundamental level of brain studies in the hierarchical framework of brain/intelligence science, which studies primitive forms and mechanisms of the natural intelligence at the neurological level towards those of brain informatics at the physiological level, cognitive informatics at the functional level, and abstract intelligence at the logical level (Wang, 2007c, 2013a; Wang and Fariello, 2012).

Figure 1. The theoretical framework of brain and intelligence sciences



NI is a transdisciplinary field that studies the neurological models and neural representations of genetic information via DNA and acquired information via cognitive neurology and neurocomputation. NI encompasses theories and methodologies for neural information processing and neural knowledge representations. A set of fundamental issues such as neural models of genetic and acquired information, neural signaling theory, the neural circuit theory, and neural representation of memory and knowledge is studied in NI.

- **Brain Informatics (BI):** BI is the second level of brain studies in the hierarchical framework of brain/intelligence science, which is built on NI at the neurological level towards cognitive informatics at the functional level (Wang, 2011b, 2012c). BI is a joint field of brain and information sciences that studies information processing mechanisms of the brain at the physiological level by computing and brain imagination technologies. BI explains how the most complicated physiological organ, the human brain, is formed based on the space/time divided nervous systems according to observations in brain anatomy and neurophysiology (Woolsey et al., 2008; Carter et al., 2009; Marieb 1992; Sternberg, 1998; Dayan and Abbott, 2001; Wilson & Keil, 2001; Wang & Fariello, 2012).

It is recognized that the exploration for the brain is a complicated recursive problem where contemporary denotational mathematics is needed in order to efficiently deal with its extreme complexity. Cognitive psychology and brain science used to explain the brain based on empirical relations between stimuli/tasks and reactions in the cortices. However, the lack of a precise logical model about the brain at a higher level has prevented a rigorous explanation of the brain by losing the forest for the trees. This methodological weakness has led to the investigation into upper layers of the problem towards cognitive and abstract intelligence theories for the brain.

- **Cognitive Informatics (CI):** CI, in its narrow sense, is the third level of brain studies in the hierarchical framework of brain/intelligence science, which is built on both NI and BI at the neurological and physiological levels towards abstract intelligence at the logical level (Wang, 2002, 2003, 2006, 2007a; Wang et al., 2006, 2009a, 2011b, 2016a). CI is a term coined by Wang in the first IEEE International Conference on Cognitive Informatics (ICCI 2002) (Wang, 2002a). Beyond the narrow sense, the broad sense of CI is a overarching theory and denotational mathematical means for brain/intelligence science referring to the definition in the beginning of the paper.

CI studies the natural intelligence and the brain from both a theoretical and a computational approach, which rigorously explains the mechanisms of the brain by a fundamental theory known as abstract intelligence. CI formally models the brain by contemporary *denotational mathematics* such as *concept algebra* (Wang, 2015e), *semantic algebra* (Wang, 2013b), *behavioral process algebra* (Wang, 2007b, 2014b), *inference algebra* (Wang, 2011a), *fuzzy probability algebra* (Wang, 2015c), and *big data algebra* (Wang, 2016d). Inversely, CI theories have also paved a way to the development of the next generation brain-inspired computers known as cognitive computers (Wang, 2009b, 2012b/e).

- **Abstract Intelligence (αI):** αI is the most precise level of brain studies in the hierarchical framework of brain/intelligence science (Wang, 2009a, 2012c). *Intelligence*, in the narrow sense, is a human or a system ability that transforms information into behaviors. In a broad sense, it is any human or system ability that autonomously transfers among *data, information, knowledge,* and *behaviors*. Recent basic studies reveal that novel solutions to fundamental AI problems are deeply rooted in both the understanding of the natural intelligence (Wang, 2002, 2016a; Wang et al., 2006) and the maturity of suitable mathematical means for rigorously modeling the brain in machine understandable forms through αI and ME (Wang, 2015a/d, 2016b; Wang & Berwick, 2012, 2013).

αI is the general mathematical theories of intelligence as a complex natural mechanism that transfers information into behaviors and knowledge at the embodied neurological, physiological, cognitive, and logical levels from bottom-up aggregations or top-down reductions. The αI theory serves as the foundation for a multidisciplinary and transdisciplinary enquiry of the brain and intelligence sciences. According to CI and αI, the exploration of the brain is a highly recursive problem that continuously remains as an ultimate challenge underpinning almost all scientific disciplines. In order to rigorously explain the architectures and functions of the brain, as well as their intricate relations and interactions, systematic logical models of the brain have been sought across each hierarchical levels. αI leads to a coherent theory based on both denotational mathematical models and cognitive psychology observations, which enables the brain to be rigorously and precisely explained through the hierarchical framework of brain/intelligence science as modeled in Figure 1.

On the basis of the αI theories and the logical models of the brain, a comprehensive set of cognitive behaviors has been formally identified in the Layered Reference Model of the Brain (LRMB) by 52 cognitive processes at the layer of sensation, action, memory, perception, cognition, inference, and intelligence from the bottom up (Wang et al., 2006). The logical model of the brain and the αI theory of the natural intelligence will enable the development of *cognitive computers* (Wang, 2009b, 2012b/e) that perceive, think, inference, and learn. The theoretical and functional difference between cognitive computers and classic ones are that the latter are data processors based on Boolean algebra and its logical counterparts; while the former are knowledge processors based on contemporary denotational mathematics. A wide range of applications of the cognitive computers have been developing in ICIC (ICIC, 2012) such as *cognitive robots* (Wang 2010a, 2015a/b), cognitive machine learning systems (Wang, 2016c; Wang et al., 2011, 2016), cognitive search engines (Wang, 2007a), and cognitive translators (Wang & Berwick, 2012). (This section is contributed by Prof. Yingxu Wang.)

3. COMPUTING WITH WORDS (CWW) AND INVALUENCE

There are many misconception about what Computer with Words (CWW) is and what it has to offer. A common misconception is that CWW and Natural Language Processing (NLP) are closely related. This is not the case. In fact, CWW and NLP have very different agendas. The objects of computation in CWW are propositions drawn from natural language. Such propositions are carriers of information, which are typically imprecise, uncertain and incomplete. There is a vast literature on propositions in natural languages, but the concepts and techniques which are described in this literature are not suited for use in CWW because there were formulated at the time when computers had not existed.

Underlying CWW are two postulates and two concomitant rationales.

A. Words are less precise than numbers
B. Precision carriers a cost
C. When numerical information is not available or too costly, CWW becomes necessary
D. CWW's advantages can be exploited to reduce cost, simplify design, and enhance robustness when there is a tolerance for imprecision

These rationales are the basis for some important applications where mathematical modules and precise information are put aside and simple linguistic models and fuzzy if-then rule are employed. A very simple example is stabilization of inverted pendulum which was described by Professor Yamakawa in his 1999 paper. In this paper differential equations are employed to describe a mathematical model of the inverted pendulum with classical stability theory. The traditional approach requires a high-level familiarity for control and stability theories. However, in the CWW-based approach a linguistic model is employed and linguistic fuzzy if-then rules are used to stabilize the pendulum. Low accuracy sensors are employed for measuring the state of the pendulum. The basic ideas which are employed in stabilization of the inverted pendulum can be used in many important practical applications such as ship stabilization and helicopter control.

A question which arises: What can be done when neither numerical information nor linguistic information is available? This situation will refer to as an *Invaluence*, meaning that no value can be assign to a variable. What can be employed in such situations is an approach based on the use of so called *Z-numbers*. Informally, a Z-number, Z, is an ordered pair (A, B) referring to the *value* and *confidence* of a variable X, respectively. A is an estimation of the value of X called a focal variable. B is an estimate of the goodness/correctness/reliability of A with respect to X. The same idea can apply to the definition of concept which do not lend themselves to traditional form of definition. Among such concepts are those of causality, fairness, relevance and beauty. Actually, there are many concepts which are of this type and which cannot serve as a basis for construction of theories which are rigorous and precise. It is my believe, that CWW and Invaluence will become a significant object of attention and development in coming years. (This section is contributed by Prof. Lotfi A. Zadeh.)

4. LEARNINGS AND INNOVATIONS IN SPEECH RECOGNITION IN GOOGLE

In the last ten years, speech recognition has evolved from a science fiction dream to a widespread input method for mobile devices. In this section, I describe how speech recognition works, the problems we have solved and the challenges that remain. I will touch upon some of Google's main efforts in language and pronunciation modeling, and describe how the adoption of neural networks for acoustic modeling marked the beginning of a technology revolution in the field, with approaches such as Long-Short Term Memory models and Connectionist Temporal Classification. I will also share my learnings on how Machine Learning and Human Knowledge can be harmoniously combined to build state-of-the-art technology that helps and delights users across the world. (This section is contributed by Dr. Françoise Beaufays.)

5. COGNITIVE CONVERGENCE OF INTELLIGENT CLOUD COMPUTING

The computing platforms for machine learning and cognitive computing are converging from two sides: (1) the nanoscale and (2) the exascale. At the nanoscale we observe the ascending power of GPU systems (e.g. Pascal GPU) and multi-core systems (e.g. Intel KNL Xeon Phi). At the exascale level we are experiencing new Exabyte data centers that are pushing and storing more video and imaging content than ever before e.g. Google DeepMind acquisition.

This is indeed the beginning of large scale AI applications that are now being approached from both sides, the deep learning architectures supported by new GPU hardware with larger multicore systems and exascale cloud system integration with access to Exabyte data streams. Hence, an obvious question that is getting more attention recently is: Is the network of large cloud platforms linked by gigabit interfaces beginning to exhibit more and more brain-like behavior? A prior question that attributed Internet to a brain-like system, appeared as early as 1995 when Peter Russell suggested that an increasingly active global network of densely interconnected humans would initialize the ecosystem for the next development stage in human history (Russell, 2000).

Recently, there seems to be even more evidence (Sporns, 2005) that the internet of things, supported by powerful clusters of cloud systems increasingly running machine learning applications, does indeed seem to converge to a world-wide brain-like system (Graham & Rockmore, 2011).

A crude comparison between the current state of the Internet and brain anatomy shows the following: both exhibit areas of specialization; both seem to have a modular architecture; both exhibit the same kind of plasticity, that is, large areas can be damaged without a significant effect on the overall operation; both seem to exhibit similar learning and focusing processes.

In effect, the aggregation of all the information available on the internet at any particular time may trigger diffusion (or divergence from any particular point of interest), or convergence to a particular point of interest (i.e. complete focus and attention, e.g. presidential elections). This wave like oscillation at a global scale is similar to the brain beta-band synchronization activity produced independently by the prefrontal cortex and the striatum. This causes the formation of new communication circuits which induces rapid learning. Similarly, enhanced activity in any part of the Internet or clustered cloud platforms results in new nodes and new pathway generation. This suggests the development for larger cloud platforms will be in the direction of automated self-configuration and learning. This brings us to the basic concept of Cloudets (Baciu et al., 2012). The ability to monitor and automatically redeploy resources (Baciu et al., 2015), within a cloud orchestration framework, aided by machine learning for predicting resource utilization and load rebalancing (Tudoran et al., 2016) makes the Cloudet architecture ideal for exploring the cloud vs brain metaphor in the context of the global Internet. (This section is contributed by Prof. George Baciu.)

6. DATA CORRELATION VS. INFORMATION DIVERSITY

In a variety of disciplines such as natural science, mathematics, engineering, and social science, statistical correlation has been used to measure similarity between two data distributions. These include Pearson's correlation in the parametric case, and Kendall's tau and Spearman's rho for ranking correlation. More recently, in the new field of information and computer science such as machine learning (ML), data mining (DM), artificial intelligence, and information fusion, information diversity has to be defined in order to measure similarity (or dissimilarity) between two variables (attributes, features, parameters, indicators, and so on) or two systems (forecasting systems, ML systems, DM systems, models, and so on).

Cognitive diversity, as defined in (Hsu et al., 2006, 2010) using rank-score characteristics (RSC) function to measure the dissimilarity between two scoring systems. It has been used in several domain applications including visual cognitive systems (Batallones et al., 2015), information retrieval systems (Hsu & Taksa, 2005), target tracking (Lyons & Hsu, 2009), skeleton pruning, feature selection in protein structure prediction, and virtual screening (Yang, 2005). (This section is contributed by Prof. D. Frank Hsu.)

7. PERSPECTIVES ON COGNITIVE COMPUTING, BIG DATA COGNITION, AND MACHINE LEARNING

The AlphaGo deep learning system represents a recent breakthrough in AI, which has defeated human experts in Go games based on deep learning and big data techniques. This event has demonstrated a bright perspective on cognitive computing based on big data. It also triggered strong interest among researchers on big data based learning. Although the term "big data" is relatively new, the act of gathering and storing large amounts of information for eventual analysis is age old. The concept gained momentum in early 2000s when industry analyst Doug Laney articulated the definition of big data as the three Vs, i.e., Volume, Velocity, and Variety. The 3-Vs perception on big data may be extended to 5-Vs known as Volume, Velocity, Variety, Veracity, and Value. Although the 5-Vs were well expressed, some of them are not innate, independent, and some were still missing. Therefore, I propose that the characterization for big data can be modeled to include the following: Volume, Velocity, Distribution, Randomness, and Regularity. This is inline with a formal definition of big data as provided in big data algebra (Wang, 2016d): "Big data are extremely large-scaled heterogeneous data in terms of quantity, complexity, storage, retrieval, semantics, cognition, distribution, maintenance, and processing costs across computer science, information science, cognitive informatics, web-based computing, cloud computing, social networks, and computational intelligence." (This section is contributed by Prof. Guiming Luo.)

8. BASIC RESEARCH ON SELF-DRIVING

In this statements, we focus on driver's behavior based on real-time data collected by driving recorders. We treat the cognitive inference function on driving behaviors as meta-cognition. Using the meta-cognition, we can find out the characters of drivers behaving on highways. By comparing the simulation results with driving recorder data, we have identified driver's cognitive processes on highways such as driving in the same lane, curve negotiation, and lane changing. In order to carry out the driving experiments in real-world conditions, we adopted a simple driving recorder widely available. The driving data were collected in a Toyota on the highway from Meguro to Nagano in Japan. This study can successfully recognize driver behaviors and maneuvers in real-time on the highway, which will lead to the design of next generation of self-driving systems learnt from human drivers. (This section is contributed by Prof. Fumio Mizoguchi.)

9. COGNITIVE COMPUTING AS A PATH TO REAL COGNITION AND ARTIFICIAL INTELLIGENCE

I strongly believe that cognitive computing with its attempts to add understanding in the computer to what it is doing is the only way to understand, formalize, represent and compute human intelligence. I have no particular interest in trying to emulate human intelligent processes unintelligently, and along with other older scholars, including several former leaders and founders of machine learning, I lament the massive turn away from the big issues in cognitive science and artificial intelligence.

I understand that it is easier to try and exploit a method further and further but I wonder whether there is any use in doing it without spending as much or more effort on understanding what this method can yield. The crucial question in my world of natural language understanding is what a text means. Can a statistical method even begin to answer this question? No, it can't, so the answers that can be produced, namely, whether Text A and Text B belong to the same group are allowed to replace, unchallenged, what needs to be asked, and text analytic and other intelligent applications remain woefully inadequate.

Meaning is unattainable without representing the human knowledge of the world, a task for which first-order logic is not sufficient. Real semantic interpretation of language entities is in the isomorphism between large property-rich ontology capturing the objects of the world and relations among them. We have developed the prototype of such an ontology and implemented several applications in it. Our rule- and meaning-based approach is where efforts in cognitive science and artificial intelligence should be redirected, and cognitive computing is the way! (This section is contributed by Prof. Victor Raskin.)

10. BIG DATA NEEDS COGNITIVE COMPUTING

Big data will be a hot topic in this decade. The development of sensors and computers enables us to acquire or store big data anywhere and anytime, which may be used for future problem solving and decision making. One of the major branches in big data analytics is how to deal with big data generated by service information system. With computerization of services, medical and healthcare services have been introduced in order to not only enhance the productivity of service entries, but also generate a large amount of services logs as “big data”. Reuse of such data becomes two-fold: one is to reuse the results of service to gain better quality of decision making; and the other is to use the historic data to optimize the efficiency of services. For example, a hospital information system (HIS) collects up to 6TP big data, which are very difficult to grasp the whole status of a certain patient in a comprehensive way.

Therefore, processing such big data needs human-like interpretation before the visualization and analysis results are shown. This is a typical context requires cognitive computing. One of the most important aspects of human-like interpretation is “granulation” proposed by Lotfi Zadeh, who pointed out that human can interpret data or humans with different granular scales. Intuitively, coarse scale gives a global view of data, while fine scale provides the precise view. Zadeh discussed that topology may play a central role in granulation. Thus, granular computing becomes a part of cognitive computing especially in the case of medical big data analytics. (This section is contributed by Prof. Shusaku Tsumoto.)

11. LEARNING THROUGH OVERCOMING INCONSISTENCIES

Perpetual learning, also known as life-long, continuous, or never-ending learning, is a research direction in the field of machine learning (Mitchell, 2006). It is concerned with how to develop computing systems that can automatically, consistently and continuously improve their performance at tasks over time. Perpetual learning is an essential capability for long-lived intelligent agents (natural or artificial) to adapt to complex, dynamic and changing environments for their survival. This capability is indispensable for the following reasons: (a) the initial knowledge in an agent’s knowledge base cannot anticipate all possible situations that the agent may find itself in; (b) the agent cannot foresee all changes in its environment over time; and (c) there are circumstances where it is difficult for the agent to follow a predefined algorithm for a given problem, so it has to rely on learning approaches.

A perpetual learning agent can be defined through its *STEP* dimensions as follows:

Given S as a set of learning stimuli, T as a set of tasks, E as type of experience, and P as performance metric, a computing system perpetually learns with regard to (S, T, E, P) if the system automatically, consistently and continuously improves its performance P at T, following S and E over time.

The primary objective of such agent systems is to satisfactorily perform tasks in *T*. Perpetual learning is just the means for agents to get progressively better, as measured by *P*, through *E* at *T* over time.

There are many types of learning stimuli. For instance, inconsistent phenomena (or uncertainties, anomalies, surprises, conflicts, peculiarities or outliers) that manifest themselves at various granularities of knowledge content (from data, information, knowledge, meta-knowledge, to expertise) can serve as learning stimuli. Henri Poincaré once said that contradiction is the prime stimulus for scientific research (Gotesky, 1968). This statement succinctly captures the essence of what contradictions or inconsistencies can help reveal, and the role they play in helping advance scientific knowledge. Inconsistencies can serve as effective stimuli to learning because they often signify the inadequacies, gaps, deficiencies, or boundary conditions in an agent's problem-solving knowledge (Wang et al., 2011; Zhang, 2009, 2010, 2011; Zhang & Gregoire, 2011; Zhang & Orgun, 2012, 2013). What the agent possesses in its knowledge base cannot properly and adequately handle the task at hand; hence a subsequent learning episode is in order.

Once an inconsistency is identified, a learning episode ensues. Some inconsistency-specific heuristics can be used to overcome the contradiction. Through the process of overcoming an inconsistency, the agent is able to revise, refine, or augment its existing knowledge to adapt to the emergent patterns and behaviors as exhibited by the inconsistent circumstance. Learning is essentially embodied in the process of finding ways to overcome inconsistent phenomena (Zhang, 2012, 2013, 2014, 2015; Zhang & Lu, 2012). The goal is to incrementally improve the agent's problem-solving performance over many such learning episodes.

The STEP learning agents can be characterized as follows: (a) Learning is triggered by stimuli, events or circumstances in which an agent is unable to satisfactorily carry out tasks in T. Learning stimuli serve to signify the inadequacy, gaps, deficiencies, or boundary conditions in an agent's problem-solving knowledge. The agent could not adequately handle T, and P is at stake. (b) Learning takes place in discrete episodes. When an agent system can satisfactorily handle its tasks in T, the need for learning is not necessarily imminent and can be deferred. The life span of an agent can be considered as an alternating sequence of task-performing episodes and learning episodes. (c) Stimulus-specific learning algorithm(s) must be deployed in each learning episode to address the task-performing deficiencies as exposed by the stimulus, e.g., to overcome the specific inconsistent phenomenon. Different learning episodes may require different stimulus-specific algorithms to handle different stimuli. (d) The outcome of a learning episode is that an agent's knowledge at T is refined or augmented just enough so that the agent won't be "startled" by the same/similar event or circumstance that triggered the learning episode. The incremental performance improvement as measured by P is accomplished by the agent's refined knowledge: it knows how to handle the task under the same circumstance next time. (e) The perpetual learning capability is embodied in the open-ended nature of such alternating sequence of task-performing episodes and learning episodes. (This section is contributed by Prof. Du Zhang.)

12. CONCLUSION

This paper has summarized a set of position statements presented in the plenary panel (Part II) of IEEE ICCI*CC'16 on *Cognitive Informatics: Perspectives on Cognitive Computing, Big Data Cognition, and Machine Learning* contributed by invited panelists who are part of the world's renowned scholars in the field of cognitive informatics and cognitive computing. It has been elaborated that the theoretical foundations underpinning brain/intelligence science and cognitive computing are cognitive informatics, abstract intelligence, denotational mathematics, and mathematical engineering. A wide range of theoretical breakthroughs and engineering applications have been reported such as cognitive informatics theories, cognitive computing methodologies, cognitive robots, computing with words, deep learning machines, cognitive learning engines, cognitive systems, cognitive knowledge bases, cognitive engineering, and cognitive self-driving cars.

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