# Chapter 20

# New CICT Framework for Deep Learning and Deep Thinking Application

**Rodolfo A. Fiorini**

*Politecnico di Milano University, Italy*

## ABSTRACT

*To achieve reliable system intelligence outstanding results, current computational system modeling and simulation community has to face and to solve two orders of modeling limitations at least. As a solution, the author proposes an exponential, pre-spatial arithmetic scheme ("all-powerful scheme") by computational information conservation theory (CICT) to overcome the Information Double-Bind (IDB) problem and to thrive on both deterministic noise (DN) and random noise (RN) to develop powerful cognitive computational framework for deep learning, towards deep thinking applications. In a previous paper the author showed and discussed how this new CICT framework can help us to develop even competitive advanced quantum cognitive computational systems. An operative example is presented. This paper is a relevant contribution towards an effective and convenient "Science 2.0" universal computational framework to develop deeper learning and deep thinking system and application at your fingertips and beyond.*

## INTRODUCTION

Data, information, knowledge, and intelligence are the four hierarchical layers of cognitive objects in the brain and cognitive systems from the bottom up. Cognitive Informatics (CI) is a transdisciplinary enquiry of computer science, information sciences, cognitive science, and intelligence science that investigates into the internal information processing mechanisms and processes of the brain and natural intelligence, as well as their engineering applications in cognitive computing. The LRMB (Layered Reference Model of the Brain) (Wang et al., 2006; Wang, 2012) provides an integrated framework for modeling the brain and the mind. LRMB also enables future extension and refinement of the CPs (Cognitive Processes) within the same hierarchical framework. LRMB can be applied to explain a wide range of physiologi-

cal, psychological, and cognitive phenomena in cognitive informatics, particularly the relationships and interactions between the inherited and the acquired life functions, those of the subconscious and conscious CPs, as well as the dichotomy between two modes of thought: "System 1", fast, instinctive and emotional; "System 2", slower, more deliberative, and more logical (Kahneman, 2011).

Nevertheless, the performance of artificial systems is still very far from the requirements of robustness, compactness and autonomy, necessary for a meaningful and skilled interaction with the external world. The latest example comes from Novartis where deep machine learning tools are vastly applied. On August 2016, Novartis dissolved its high-profile cell and gene therapy unit operating under the guiding hand of Usman "Oz" Azam (Reuters, 2016). Usually, this is the final result of research planning based on assumed trustworthy mathematical tools that they are not, unfortunately. According to physicist Jose G. Vargas "All physical concepts are to be viewed as emergent. Emergence of this type and reductionism are as inseparable as the two faces of an ordinary surface. In advanced research, failure comes from lacking of effective and reliable mathematical model and tools to deal with system emergent behavior" (Vargas & Torr, 2015).

Furthermore, a "human-scale" simulation with 100 trillion synapses (with relatively simple models of neurons and synapses) required 96 Blue Gene/Q racks of the Lawrence Livermore National Lab Sequoia supercomputer, and, yet, the simulation ran 1,500 times slower than real-time. A hypothetical computer to run this simulation in real-time would require 12 GW, whereas the human brain consumes merely about 20W. Why this disparity?

Biological evolution developed computational strategies for making sense of the external noisy and ambiguous signals to produce appropriate behavior in real time, at the lowest possible energetic cost and using an inhomogeneous substrate for computation comprising slow and optimized elements. That is the main reason why neuromorphic engineering (NE) approach is receiving a lot of interest.

While future enabling nanotechnology is underway, current NE approaches are focusing on two factors mainly: technology and architecture. Architecture innovation, specifically, focuses on minimizing the product of power, area, and delay in a system that could be implemented in today's state-of-the-art technology.

It is interesting to note that optimized information representation and conservation, taking into consideration the interrelationships between data, information, knowledge, and intelligence, can play a fundamental and strategic role to overall system computational energy minimization. Nevertheless, just a few pioneering attempts are under way. We present one of them. To better understand the differences of our approach from traditional ones, we need a quick overview of current systems major limitations first.

## CURRENT SYSTEMS OVERVIEW

Traditional machine learning (ML) approach is based on a two-part system usually: feature extraction and selection module plus trainable classifier module. Since the early 1930s, when Nicolas Rashevsky developed the first model of neural network (McCulloch & Pitts, 1943), many of us have been practicing with artificial neural networks (ANNs) derived or not derived from biological neural networks (BNNs) for decades. Some others have started after convolutional neural networks (CNNs) and deep learning (DL) showed their amazing impact on applications. Some others are following the Big data and data analytics mood.

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