

# The ULC Project

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**Abstract**—The ULC (Universal Learning Computer) project is based on the general proposition that a system capable of learning to simulate a broad range of human cognitive functions can have a significantly simpler formal representation than specialized systems aimed at simulating small subsets of such functions.

## I. PROBLEM STATEMENT

The concept of a Universal Learning Computer (ULC) is inspired by the example of the human brain. The human brain has many remarkable cognitive characteristics that deeply puzzle scientist and engineers. These characteristics include:

- 1) Broad universality as a learning system – we can learn to perform, in principle, any mental computations.
- 2) Context-dependent dynamic reconfigurability - we can change our attitude (mental set) to match a combinatorial number of different situations (contexts).
- 3) Very large hierarchical context-sensitive associative memory displaying effects of short-term memory (STM), intermediate-term memory (ITM), and long-term memory (LTM).
- 4) An ability to learn to perform active hierarchical context-dependent pattern recognition.
- 5) An ability to learn to perform hierarchical context-dependent motor control.
- 6) Working memory and mental imagery. An ability to learn to mentally simulate different external systems.
- 7) System of motivation involving emotions. An ability to form context-dependent concepts of “good/bad,” “important/unimportant,” etc. in the course of learning.
- 8) Activating system and attention. An ability to learn to pay attention and to wait.
- 9) An ability to learn by imitating actions of other people.
- 10) An ability to learn a natural language – the most unique and puzzling property of the human brain.

Conventional (von Neumann) computers and universal Turing machines [1] are examples of *universal programmable* computing systems. These systems can be programmed to simulate, in principle, any deterministic behavior. (With a random number generator, these systems can simulate any probabilistic behavior as well.) However, the way of programming these systems doesn't match our intuitive notion of *associative learning* as applicable to the human brain.

Some of the known artificial neural network (ANN) models seem to qualify as brain-like associative learning systems. However, these systems are not universal in Turing's sense and can be trained to perform only rather limited types of behavior. For example, the general level of computing power of the Perceptron-like feedforward neural networks doesn't exceed

that of combinatorial machines (Boolean logic). Accordingly, the level of computing power of such systems with a delayed feedback (the, so-called, recurrent neural networks) is not greater than that of finite-state machines (Chomsky's type 3 [2]).

In contrast, an adequate computational model for the human brain must be a learning system with the highest general level of computing power (type 0). This follows, for example, from the observation that a person with a good visual memory can learn to perform, in principle, any mental computations by mentally writing symbols on an imaginary piece of paper. The practical limitations on the size of working memory are of no principle importance. It is the way the system uses its memory, rather than the size of this memory, that determines the system's general level of computing power.

- *How can a computing system universal in Turing's sense (type 0) form an arbitrarily complex software in the course of learning?*
- *How can such system dynamically reconfigure its software to match a combinatorial number of possible contexts?*
- *What is the possible architecture of a ULC combining all cognitive characteristics mentioned in items 1-10?*
- *How can the above ULC be efficiently implemented as a neurobiologically plausible neural network model?*

I argue that, unbelievable as it may sound, a brain-like ULC capable of learning to simulate a broad range of human cognitive functions can have a significantly simpler formal representation than specialized systems aimed at simulating some small subsets of such functions. That is, attempts to *artificially* reduce the *natural* dimensionality of human cognitive problems – to simplify these problems! – make the problems more difficult (unsolvable). Such “simplifications” are penalized by the “curse of dimensionality.”

To get a preliminary intuition as to how a “whole” physical phenomenon can have a simpler formal representation than the “parts” of this phenomenon, consider the example of the Maxwell equations. There exists an efficient formal representation of the behavior of the “whole” electromagnetic field. In non-trivial cases, however, it is impossible to find separate formal representations of the electric and magnetic “parts” of this behavior. It was suggested ([3],[4]) that a somewhat similar general relationship exists between the “whole” human context-dependent behavior and the “parts” of this behavior corresponding to different contexts – it takes a combinatorial number of such “single-context-parts” to represent the “whole” context-dependent behavior. This problem of “attitude and

context” was first raised in [5].

A good survey of the complexity theoretic results related to ANNs can be found in [6] (see also [7], and [8]). It should be emphasized that theoretically interesting notion of super-Turing computing is not applicable to systems with noise. Accordingly, it is safe to say that no real computing system can exceed the general level of computing power corresponding to the class of Turing machines (type 0). The practically important question addressed by the ULC project is how a system with the highest level of computing power can learn to perform behavior of type 0. It can be shown that a learning system employing an error minimization learning algorithm – such as, for example, backpropagation – cannot learn to perform behavior of type 0.

## II. CURRENT RESEARCH

The proposed ULC is arranged on the principle of E-machine ([3],[4],[9],[10],[11],[12]). An E-machine is a complex associative learning system built almost entirely from interacting hierarchical context-sensitive associative memories (CSAM). It was shown that the simplest universal learning E-machine – a *bare-bone* ULC – can be built from just two CSAMs. The preliminary results show that the cognitive capabilities of this class of ULCs increase dramatically with the integration of brain-like computational mechanisms. Accordingly, a powerful ULC doesn’t have to have a very complex hardware. The cognitive characteristics of such a ULC are determined largely by its software, the latter being created mostly in the course of learning. The current research includes the following tasks:

- 1) Compiling a list of basic psychological and neurobiological observations, questions, and ideas that show psychological and neurobiological relevance of the proposed concept of ULC.
- 2) Description of the components of a ULC based on the ideas selected in item 1.
- 3) Description of the possible neural network implementations of the components from item 2.
- 4) Description of the possible ways of integrating the components from item 2 into a ULC.
- 5) Description of the possible mappings of the neural network models from item 3 to different areas of the human brain.
- 6) Preparing a list of experiments for testing the proposed ULC and its components.
- 7) Simulating the ULC using computer clusters.

The ULC project belongs to the broad area of research that is defined by DARPA as the study of Biologically Inspired Cognitive Architectures (BICA). The main thrust of this research is to tackle the problem of *system integration* in neural and cognitive modelling.

## III. KEY AVENUES

The ULC project provides a natural framework for integrating a broad range of brain modelling and cognitive modelling ideas into a single computational model for the whole brain. The proposed ULC employs several massively parallel

elementary procedures that can be efficiently implemented in neural networks. These include: decoding, modulation, choice, encoding, next E-state procedure (dynamic reconfiguration), and next G-state procedure (learning). (The letter ‘E’ implies “residual Excitation”; the letter ‘G’ implies “synaptic Gain.”)

Of particular interest is the next E-state procedure – in nontrivial cases, this procedure cannot be implemented in traditional neural network models. Papers ([13], [14]) suggest that rather complex next E-state procedures can be efficiently implemented at the level of statistical conformational dynamics of ensembles of membrane proteins. I believe, therefore, that – at the level of neural modelling – one of the most promising areas of research is the study of neural networks built from complex neurons similar to those outlined in the above papers.

At the level of cognitive modelling, I am particularly interested in the following issues:

- 1) Developing techniques for real-time simulation of very large context-sensitive associative memories (time step on the order of 10msec).
- 2) Developing techniques for real time simulation of ULCs built from several CSAMs.
- 3) Developing techniques for programming (teaching) ULCs to perform different cognitive functions.

In general, I believe that it is critically important to take into account simultaneously both *neurobiological* and *psychological* data. Ignoring psychological data leads to the, so-called, “mindless brains” – the systems that simulate neurobiological effects, but have limited cognitive capabilities. Ignoring neurobiological data leads to the, so-called, “brainless minds” – the systems that simulate psychological effects, but cannot be implemented in a brain-like hardware.

I believe that to efficiently address the issue of system integration – in both neural modelling and cognitive modelling – we should adopt the, so-called, *scientist/engineer* approach [15]. As engineers, we should *explicitly* state that our main goal is *system integration*. Accordingly, we should evaluate the quality of our (neurobiologically and/or psychologically-inspired) designs with respect to this main goal. As scientists, we should rely on biological data to separate relevant engineering and mathematical ideas from irrelevant ones. Without such *scientific filter*, we have a good chance to go astray and spend a lot of time dealing with (interesting) mathematical and engineering problems having but little to do with our main goal. Here is an eloquent quotation from [5] expressing this methodological mental set. Wrote Zopf Jr. (1962):

*“I am intolerant of those who regard the whole of biological data of the phenomena of biological organization and intelligence as not more than a grab bag from which to abstract technological goodies. My intolerance is tempered only by the belief that such casual abstraction cannot succeed... The point is it is not a grab bag. The items therein show connection, and to attempt to draw out just one glittering generalization entails a host of contradictory loose ends.”*

## REFERENCES

- [1] Turing A.M. On computable numbers, with an application to the Entscheidungsproblem. *Proc. London Math. Society*, ser. 2, 42, 1936.
- [2] Chomsky, N. Three models for the description of language. I.R.E. *Transactions on Information Theory*. JT-2, pp. 113-124, 1956.
- [3] Eliashberg, V. The concept of E-machine and the problem of context-dependent behavior. *Txu 40-320, US Copyright Office*, pp1-158, 1979.
- [4] Eliashberg, V. The concept of E-machine: On brain hardware and the algorithms of thinking. *Proceedings of the Third Annual Meeting of the Cognitive Science Society*, pp. 289-291, 1981.
- [5] Zopf, G.W., Jr. Attitude and Context. In "Principles of Self-organization", *Pergamon Press*, pp. 325-346, 1962.
- [6] Šima, J., and Orponen, P. General-Purpose Computations with Neural Networks: A Survey of Complexity Theoretic Results, *Neural Computation*, 15, pp. 2727-2778, 2003.
- [7] Maclennan B.J. Transcending Turing Computability, *Minds and Machines*. vol 13, No 1, pp. 3-22, 2003.
- [8] Siegelman, H.T. Neural and Super-Turing Computing, *Minds and Machines*. vol 13, No 1, pp. 103-114, 2003.
- [9] Eliashberg, V. Context-sensitive associative memory: "Residual excitation" in neural networks as the mechanism of STM and mental set. *Proceedings of IJCNN-89*, Washington, D.C. vol. I, pp. 67-75, 1989.
- [10] Eliashberg, V. Universal learning neurocomputers. *Proceedings of the Fourth Parallel Processing Symposium*, Fullerton, CA, pp. 181-191, 1990.
- [11] Eliashberg, V. A relationship between neural networks and programmable logic arrays. 0-7803-0999-5/93, IEEE, pp. 1333-1337, 1993.
- [12] Eliashberg, V. What Is Working Memory and Mental Imagery? A Robot that Learns to Perform Mental Computations. *Web publication*, [www.brain0.com](http://www.brain0.com), pp. 1-31, 2002.
- [13] Eliashberg, V. Molecular dynamics of short-term memory. *Mathematical and Computer modeling in Science and Technology*, vol. 14, pp. 295-299, 1990.
- [14] Eliashberg, V. Ensembles of membrane proteins as statistical mixed-signal computers. *IJCNN 2005 Proceedings*, 2005.
- [15] Church, G.M. From systems biology to synthetic biology. *Molecular Systems Biology*, *web publication*, [www.nature.com](http://www.nature.com), doi: 10.1038/msb4100007, pp. 1-3, 2005.