"Logic, science and complex systems - a synthesis view"

Yuan Yan Chen

There have been many important new developments of mathematical science in the last few decades; among them are fractals/chaos, neural networks, and fuzzy systems. These developments are mostly due to the invention of the computer. With the computer it also exposes its limitation to mimic the brain function. From our current understanding, the brain seemed to take advantage of both analog and digital computations. The brain extracts the pattern in the world. Since we never step over the same river twice; precision becomes an encumbrance, the concept of physical state can be stretched to a field or manifold.

These developments assert the viewpoint of Kelly (1955),

"Our psychological geometry is a geometry of dichotomies rather than the geometry of areas envisioned by the classical logic of concepts, or the geometry of lines envisioned by classical mathematical geometries."

A decade ago, I have found a way to unify probability theory and fuzzy set theories into a single framework of statistical inference. In the process I helped to make fuzzy set measurement objective, i.e. the fuzzy set membership can be estimated from data. Recently I have combined neural networks and fuzzy systems, which has shed light onto the mystery of how the brain's higher order cognition network is organized and is computed. Now the brain's higher order cognition can be linked to lower levels of the perception system, and therefore be understood. *Plausible Neural Network* (PNN) was developed to demonstrate the propriety of this approach.

I have found that this computation can be applied to model dynamic systems with the interaction of many components. If a system has identical components and uniform interaction strength, it still might undergo some interesting self-organization. An example of this is the Ising ferromagnetic model in statistical mechanics, which has been linked to the simplest neural network model. If the interaction strengths are uneven, a complex system is created. A complex system has too many basins of attractions to be computed by traditional statistics or differential equation. The brain is such a system, where each basin of attraction is a memory. Thus, some researchers call it a liquid state machine; the flow of thoughts is like a river, with many tiny swirls.

Computation of a physical system can be characterized by the transformation from potential energy to kinetic energy (cf. Mead (1987)). In electric circuits it is the transformation of voltage to signal, while in neurons it is the transformation from membrane potentials to spikes or nerve impulses. The transformation from stationary state into motion requires the potential energy to exceed a certain threshold. For, example, the membrane potential of nerves is stationary as long as the stimulating current remains below a critical threshold; if this critical value is passed, the membrane potential rises rapidly, resulting in nerve impulses. This is considered as a bifurcation in a nonlinear dynamic system.

In statistical inference, the data evidence corresponds to membrane potentials, and the nerve impulses correspond to the logical values. The neuron that receives substantially higher data evidence in comparison with its rival hypotheses becomes the winner and fires the nerve impulse. Thus, our belief judgment is formed under the organization of the Winner-Take-All (WTA) circuits (Chen and Chen (2004)). Thus the natural *law of thought* is belief logic and not Boolean logic. A consequence of such logic is that truth is always relative; scientific theory and our model of the world are just a consensus belief of the society and are always modifiable with new hypotheses and data evidence.

In general we can distinguish two kind of logical inferences, one is deductive and the other is inductive. If we start up with a hypothesis, which can be a theory, an axiom or a model (deterministic or stochastic), all the inference derived from it is deductive. Based on deductive inference, we can perform an experiment to see if it fits the observations (data), and a hypothesis is indirectly verified. However, if there are rival hypotheses that also produce similar results, we have difficulty in judging which hypothesis is the truth. We will need to await more data observations to make a judgment. Our scientific theories progress along this direction. In general we choose the theory based on its simplicity, generality and consilience.

If we start from the data observations and extract statistical regularity (pattern) to create an implicit model, then it becomes an inductive inference. We can use this implicit model to further deduct inference under a similar situation. Our brain uses a lot of this kind of inference; there is no mathematical function or equation in our mind. We use further observations to refine our model, and in the mean time we use this not so perfect model as our guidance. All learning, especially in the early childhood, starts from inductive inference and differentiation of patterns; this is called self-organization or unsupervised learning in neural network.

Our description of the world is based on dynamics of a system, which represents the evolvement of the physical state. Most nonlinear dynamics do not have a direct analytic solution; to obtain a solution it requires some kind of iterative computation. In differential equations, it is based on numerical approximations or gradient descent. In statistics it is based on the Expectation Maximum likelihood (EM) algorithm. However, all complex systems are nonlinear. Thus our brain utilizes nonlinear computation to understand our environment. *Plausible Neural Network* (PNN), is the simplest EM algorithm ever developed to compute a dynamic system. Thus, I believe it can allow us to study much larger scale dynamic systems, which is impossible to compute with the other current methods.

Each branch of science has progressed up to a point where each system has been decomposed into finer and finer components. Perhaps the next step is to understand how the components in the systems interact, communicate and self-organize. Several obstacles prevent us from progressing in this direction. First, what is the principle of self-organization? Secondly, even if we can model large-scale systems, with each component interacting with each other, how can its dynamics be computed and understood?

It is evident from recent papers in Nature and Science that researchers are attempting to understand the computational rules governing nature.

Science: **“Uses and Abuses of Mathematics in Biology”**.

http://www.sciencemag.org/cgi/content/full/303/5659/790

Nature: “**Do Plants Act Like Computers**”

http://www.nature.com/nsu/040119/040119-5.html

“Some scientists even think that distributed computation is fundamental to the way the world works. In his book A New Kind of Science, mathematician Stephen Wolfram argued that the laws of physics might arise from units of matter, space and time interacting with one another according to simple rules He showed that so-called cellular automata - simple, discrete 'particles' programmed to switch between different states depending on the states of their neighbors - can mimic computers.”

Wolfram is right when saying the mathematical equation is powerless; starting from three particles, the dynamics is already chaotic and has no analytic solution. He is also right about complex system following a simple rule. The WTA gate in neural computation is an example. He proposed that the basic physical law is a network computation with infinitesimal small discrete space and time. The problem of considering nature computation as cellular automation is that it is based on the concept of parallel digital computation, which is too narrow. Once you set up the program (rule), then it will run, but there is no explanation where the rule comes from, and how the rule can be changed.

By understanding how neural networks compute, learn, and are organized, I realized that this could be the underlying principle of many self-organizing and adaptive systems. Competitive network is based on negative feedback, which is very common in every scale of biological systems. Learning is an adaptive behavior, which depends on repetitive stimuli from the environment. The brain is the fastest adaptive system, since it has synapses to store the environment data information, and can change its dynamics easily. Other biological systems also have adaptive behavior; they are just not as noticeable.

Reference

[1] Chen, Y. Y. and Chen, J. J. (2004). Neural networks and belief logic, *Proceedings of the Fourth International Conference on Hybrid Intelligent Systems (HIS'04), IEEE.* 460-461.
[2] Kelly, G. A. (1955). *The Psychology of Personal Constructs.* New York: Norton.
[3] Mead, C. (1989). *Analog VLSI and Neural Systems.* Addison-Wesley.