Introduction to the special issue on goal-directed neural systems

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Introduction

What does genuinely intelligent behavior require? All definitions of intelligence include not only successful achievement of predetermined goals but being able to set one’s own goals.

Thus far, in the development of both artificial and biological neural networks, there has been more work on the achievement of predetermined goals than on setting goals. This is true both because achieving existing goals is easier than setting new goals and because of the influence on researchers of psychological notions such as instinct and stimulus–response. Yet as the brain has become more complex, the architectures for satisfying evolution-based drives have gradually expanded into architectures capable of evaluating both the external environment and the body’s internal states, and using their evaluations to select courses of action. The same capabilities have also gradually entered into artificial neural systems used for diverse applications including pattern recognition, robotics and navigation, prosthetics, and video game design.

This special issue is an offshoot of a post-conference workshop on Intentional Neural Systems at the August 2005 International Joint Conference on Neural Networks in Montreal. The workshop was followed a year later by a two-day conference on Goal-Directed Neural Systems with many of the same speakers, held in October 2006 at Arlington, Texas, and jointly sponsored by the Texas SIG of the International Neural Network Society (INNS), the Metroplex Institute for Neural Dynamics (MIND), and the University of Texas at Arlington. After the editors-in-chief of Neural Networks approved our proposal for a special issue based on updates of presentations given at the Arlington conference, we invited several additional authors who did not attend the conference but had made important contributions to the theme of the issue.

The change from the term “intentional systems” to “goal-directed systems” was made to avoid potential concerns about whether or not artificial neural systems could possess conscious intentions. However, intentionality remains an important consideration in many of the articles in this special issue. In much of the work discussed here there is a fine line between intentionality and control, and it is hard to know where one ends and the other begins.

The interconnections and cross-links between different articles in this issue are numerous. Similar themes appear whether the aim of the work is predominantly theory, cognitive science, understanding of the brain, or development of engineering applications. Yet we have been able to divide the articles into four sections whose predominant emphases are, in turn, theoretical, cognitive, neuroscientific, and applied.

Articles in this special issue

The general theory section starts with the article by Werbos, which has a strong historical flavor and explicitly ties together the two different aspects of goal-directed neural activity. He states that the function of prediction comes first in evolution (at the level of simpler vertebrates like fish and amphibians) and only at the level of mammals do we evolve the additional layers of the cortex required for the function of creative suggestion. He lays out in stages a somewhat parallel evolution from prediction and control toward active goal generation and planning in his own models, and those of other investigators he has been closely connected to (e.g., Sutton and Barto) for over forty years. The main body of his article deals with generation of a mouse brain, with an appendix to describe additional mechanisms needed for a human brain. Finally, he discusses applications of both the mouse and human brain theories to electric power systems.

Theoretical connections between apparently “lower-level” and apparently “higher-level” mental functions are also major themes of the next three articles: one by Dayan and two by Zhang. Dayan considers various dichotomies that have arisen in psychological and computational theories of behavioral control. These include model-based versus model-free; declarative versus procedural; interdependent versus independent; interpreted versus compiled; prior-bound versus data-bound; and instructed versus learned. He relates all these dichotomies to the difference between cortical and subcortical – specifically, prefrontal cortex versus basal ganglia – control in the brain, and to various “System 1 versus System 2” theories inspired by the ground-breaking findings of characteristic human irrationality by Tversky and Kahneman. He shows that the two forms of control are in fact closely linked together, although “System 1” which involves causal propensities ultimately controls “System 2” which involves statistics.
Zhang further develops the potential unity between levels of control with his mathematical theory of selectionism and Bayesianism. In his first article, he starts with the dichotomy between selection-by-consequence, whereby animals increase or decrease the probabilities of particular actions after experiencing their consequences (the law of effect), and Bayesian estimation, whereby deciders explicitly update assessed probabilities of consequences based on a statistical formula. Despite the difference in information gathering methods for the two types of selection, Zhang shows mathematically in the first of his two articles that modifications of action probabilities in the selectionist framework actually follow Bayesian dynamics. The second article applied the analysis of the first article to solving the sequential temporal credit assignment problem for a chain of operant actions, a problem popularized by Sutton and Barto.

Vrabie and Lewis develop a mathematical theory of adaptive optimal neural control. They show that reinforcement learning with an actor-critic structure can solve optimal control problems for a nonlinear system without explicitly knowing the system's internal dynamics. They call their technique policy iteration, and describe it as a reinforcement learning algorithm that alternates between the steps of policy evaluation and policy improvement. They prove several convergence theorems about their method and exhibit some simulations for specific nonlinear systems with known optimal cost functions and known optimal controllers.

The next few articles apply insights about goal-directed neural systems to some outstanding problems in cognitive science. Perlovsky applies his established theory of dynamic logic to understanding the interface between language and cognition. In dynamic logic (also known as neural modeling fields), the network or organism develops ever more accurate models of the environment under the influence of signals based on the discrepancy of the previous models from the world. Compared with other animals, humans are able to develop more accurate models at higher levels of abstraction due to the development of language and the consequent ability to label and categorize events. Yet even though language is later in evolutionary development than are other aspects of cognition, the models developed in the language system become crisper than those in the cognitive system, which explains why children with highly developed vocabularies still are not able to act like adults. Perlovsky states that the existence of the “dual hierarchy” of language and cognition has not yet been verified in the brain but points to some recent imaging results that suggest possible mechanisms for such a hierarchy, and for its interactions with emotion and instinct.

Ward and Ward deal with the problem of representation, which has stirred a fair amount of philosophical debate. While they note that the PDP modelers have used the term “internal representation” for any sort of hidden unit that learns a characteristic set of responses to input patterns, their use of the term is more restricted. Based on the definitions propounded by the philosophers Clark and previous neural network studies by Beer, they confine the term “representation” to the property of an agent with internal configurations that are understandable related to objects in the environment and that are used in a task-relevant manner even when those objects are not visible to the agent. Ward and Ward utilized genetic algorithms to evolve a shape discrimination network that had this functional representation property in the sense of both Clark and Beer.

Kwon and Choe deal with general neural network mechanisms for prediction and specifically the effects of time delays. They point to mathematical results showing that time delays can lead to oscillations in the system that might interfere with the function of prediction. They add to some of their previous model networks some neuronal facilitation and find that it can overcome the oscillations caused by time delays. The resulting network is found to perform effectively on a two-dimensional pole-balancing problem. In their discussion they suggest future further extensions of the network that involve anticipation of the possible neuronal delays in the system, which would be useful for a more proactive type of goal direction.

The articles in the third set within our special issue apply goal direction ideas to the modeling of brain region involvement in specific behavioral processes. Kozma and Freeman apply chaotic dynamics and phase transitions to modeling of cortical-subcortical interactions in decision making. Their KIV model (latest in a series of “K” models named after the neural network pioneer Aharon Katchalsky) is designed to simulate intentionality by phase-locking sensory and motor areas for short time periods to the emotional regions of the limbic system. Kozma and Freeman’s current model builds on previous models that have been successful in pattern recognition, developing attractors that represent gestalts consisting of internal and external sensory signals, and they point toward future extension in which the frames are globally integrated, leading to high-level intentionality and consciousness.

Levine approaches neural bases of decision making with a theory based on nonlinear shunting differential equations, competitive-cooperative dynamics, and adaptive resonance. Building on his own previous work along with that of Perlovsky, Carpenter, and Grossberg, he addresses the issue of how both heuristic (or intuitive) and deliberate (or logical) decision rules can coexist within the same brain. For clues he turns to the brain’s heritage of subcortical drive representations shared with other mammals, which (at least in primates) includes not only physiological drives for food, water, and sex but drives for pleasurable stimulation, knowledge of the environment, and self-actualization. He points to brain imaging studies that find different brain activation patterns in those that deal logically with a problem versus those that follow nonrational heuristics. Levine also considers how the brain’s executive system decides (imperfectly) which type of rule is most appropriate for a given context.

Kim, Hwang, Seo, and Lee deal with frontal lobe involvement in decision making from the viewpoint of reward maximization. They show that neuronal responses in the lateral prefrontal cortex of rhesus monkeys fairly accurately code the expectation of reward, and that these neurons discount rewards based on delay using a particular mathematical discounting function (hyperbolic). Kim et al related the neuronal firing patterns to the animal’s previous choices and the outcome of those choices, suggesting that in monkeys as well as humans the prefrontal cortex performs an executive function that involves updating and manipulation of working memories. They draw some instructive comparisons between their work and both reinforcement learning theories and economic utility theories, emphasizing that those theories in their present forms do not capture the full complexity of the brain’s decision making functions.

The last three of the special issue articles apply adaptive goal direction techniques to engineering problems. Sanchez, Mahmoudi, DiGiovanna, and Principe discuss their work on building neuroprosthetic devices: after reviewing the possible applications to sensory and cognitive disabilities, they focus on devices for people with motor disabilities. They show how recent advances in neuroscience and engineering have enabled the building of devices that can co-adapt with their human users and even help their users to set goals. They develop a theory for how the prosthetic devices need to keep track of neuronal patterns in the motor and parietal cortices of human users, thereby being able to adapt both to the user’s current location and his or her goals and intended movements. They describe promising results from experiments on interfacing their devices with rat brains.

Brannon, Seifert, Draelos, and Wunsch discuss military applications of coordinated learning. Brannon et al. note that...
unsupervised learning, supervised learning, and reinforcement learning all have long traditions of successful neural network applications, and all are useful for different situations. Supervised learning is useful for initial training and updating based on explicit information. Reinforcement is useful for on-line operational improvement when the environmental information is less explicit. Finally, unsupervised learning is useful when external labels are absent. Using ARTMAP (the supervised version of adaptive resonance) as its core, the authors demonstrate a system that combines all three modes along with a situation assessment module that decides which one of the modes to utilize in the current environment. This system is also combined with a human operator and serves for decision support.

In the last article of the issue, Kohl and Miikkulainen deal with a challenge in using genetic algorithms in a variety of control problems such as balancing and collision warning. The challenge has to do with the fractured nature of decision space, that is, the correct action changes discontinuously as the agent moves through \( n \)-dimensional space. They find two methods for dealing with this challenge of fracture. One method has to do with introducing locality of receptive fields for network nodes, and the authors remark (partly based on several other articles in this issue) that this form of locality is neurobiologically plausible. The other method has to do with cascading together several smaller networks. These methods are illustrated using computer models.

**Concluding remarks**

The similarities of issues and themes across the different articles in this issue are a striking demonstration of the interconnectedness of the whole field of neural networks (including closely related fields such as intelligent computation, computational cognitive neuroscience, and mathematical psychology). As the field matures and moves from considering algorithms to solve predetermined problems toward designing agents that set and solve their own problems, all available sources of insight become crucial. It will become increasingly important for neuroscientists, cognitive scientists, psychologists, neural engineers, and intelligent computation specialists to be cognizant of progress in each other’s fields. Also it will not be possible to understand high-level, creative process apart from low-level, instinctual or routine processes; optimal control apart from suboptimal control; rationality apart from emotionality; unsupervised learning apart from supervised learning; cognition apart from conditioning, and so forth. The vision of the early cybernetic pioneers who united brains and machines may yet be fulfilled in this century.