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Commentary on "The Nature of Distributed Learning and Remembering"

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This exposition (Iran-Nejad and Homaifar, 2000) offers a compelling argument for biofunctional cognition, which suggests that functional properties of the brain, as inferred from empirical findings, be used as a basis for examining the nature of distributed learning and remembering (DLR). Undoubtedly, cognitive models that are compatible with observed phenomena will contribute to a more complete understanding of the nature of DLR. Notwithstanding the contrasts and incompatibilities between connectionist and biofunctional models stressed by the authors, we can learn from each class of models. The issue of how to realize the latter to enable empirical investigations still remains to be addressed.

Models that are meant to express the nature of distributed learning and remembering (DLR) in the human brain should be based as closely as possible on what is understood about brain functionality and the nervous system. PDP connectionists and associationists, as well as the authors of this paper have proposed models with this characteristic in mind; however, they hold different perspectives on the nature of DLR regarding notions of what the most fundamental elements are and how they are integrated. Iran-Nejad and Homaifar (2000, this issue) present a very compelling argument for biofunctional cognition in this regard. In the paper, they advocate the study of the brain at a more comprehensive level than attempted or permitted by popular connectionist and associationist theories.

The authors point out that PDP connectionists make metaphorical use of neurophysiological concepts while avoiding close examination of the mind–brain problem. In doing so, the opportunity to learn of important phe-

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nomena that could be incorporated to strengthen models of cognition is lost. The result, in essence, is that PDP connectionist models are necessarily most artificial. The casting of PDP connectionism in this light relative to conventional cognitive science brings to mind the view of engineering as merely applied physics. Engineering approaches often employ assumptions and simplifications to arrive at working solutions or explanations that are satisfactory in some sense. Engineers often *synthesize* systems. On the other hand, pure physics-based approaches are concerned more with stark realities and full understanding of phenomena: physicists tend to more rigorously *analyze* systems. This analogy suggests that PDP connectionists take more of an "engineering approach" to the mind–brain problem. It is certainly not evident that the artificial aspects of PDP connectionist models diminish their potential to contribute to our understanding of human cognition or the mind–brain relationship. Connectionist models provide some insight (that is satisfactory in some sense) into how DLR processes might work in the brain, but only partial models at best of human cognition (Tienson, 1990). Indeed, if PDP connectionist models are somehow shown to be invalid, they will have been counter-examples of the machinery of human cognition in much the same way that the digital computer (once thought to emulate aspects of brain function) has been accepted as a counter-example of brain functionality.

The major oversight by PDP researchers of failing to consider the important work of Lashley and its implications for their models is stressed as evidence of incompatibility between the PDP perspective and Lashley's empirical contributions. Many models proposed by researchers of cognitive science and artificial intelligence fail to capture much of what is broadly accepted as fact (however limited) regarding actual brain functionality and its relationship to the mind, whether determined empirically or otherwise. Perhaps this is due to the complexities (for modeling) that arise as well as our impatience with the process required to obtain full understanding of complex phenomena. In any case, cognitive models of DLR that are compatible with observed phenomena and knowledge acquired through direct experimentation with biological systems have perhaps the strongest potential for contributing to advancements in our understanding. Biofunctional cognition may have such strong potential since it seeks to use, as a basis for examination, the functional properties of the brain without subscribing to the "engineering approach" of PDP connectionists. Moreover, Iran-Nejad and Homaifar assert that biofunctional cognition is compatible with Lashley's empirical findings and other foundational DLR research. In my opinion, among the sharpest distinctions between models of PDP connectionism and biofunctional cognition are representations, levels of abstraction, and unfortunately semantics, all of which contribute to the suggested incompatibility. In addition to the clues provided by connectionist models, it seems plausible that our models should also provide insight into how the brain organizes and utilizes knowledge to perform cognitive processes (Pylyshyn, 1980). We should seek to learn what we can from each class of models to arrive at a shared understanding of the nature of DLR and a more complete model of human cognition.

The issue of bridging the gap between mental phenomena and the nervous system is similar to the issue of integrating deliberative capabilities (e.g., planning and goal-directed activity) with reactive capabilities (stimulus–response behavior) in artificially intelligent systems such as autonomous robots and software agents. The issue is one in which phenomena at both high and low levels of abstraction share significant responsibility for system function. In the latter case, most roboticists and AI researchers now agree that intelligent autonomous systems must be endowed with both deliberative and reactive capabilities (Kortenkamp, Bonasso, and Murphy, 1998). As with mental phenomena and the nervous system, the *method* of integration of high and low level functionality is the question at hand. Only exhaustive study of phenomena at each level will lead to revelations about how the two levels are bridged or related, similar or dissimilar, necessary or sufficient, etc. in regard to brain functionality and DLR.

The biofunctional model considers both high and low levels of brain function and, as such, offers a bridge that is missing in models of PDP connectionism and conventional cognitive science. If the emerging field of biofunctional cognition is to make significant contributions, however, the issue of how to realize biofunctional models to enable empirical investigations will need to be addressed. Empirical investigations into biofunctional cognition may then reveal models of DLR that offer additional insight and explanations about the mind–brain relationship.

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