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# Resolving the Cognitive Behavioral Controversy

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The recent *tBT* article by R. P. Hawkins (1994) on doctoral students' perspectives regarding the cognitive behavioral debate illustrates that the cognition versus behavior schism (cf. Staats, 1983) exacts a continual human toll from graduate students, in addition to dividing behavior therapists in nonproductive ways. Contemporary developments in the field of learning serve to synthesize this schism by incorporating important values of both sides of this issue.

From the 1920's through the 50's, learning was scientifically studied by psychologists primarily in the laboratory. These studies largely entailed either operant (instrumental) or respondent (classical) conditioning. Recommendations were made by Eysenck (1964) and Wolpe and Lazarus (1966) to base behavior therapy on modern learning theory. Differences of opinion regarding the relevance of animal models of learning to human behavior disorders resulted in broadening the definition of behavior therapy (Kazdin, 1978), including cognitive explanations of behavior disorder.

Recent advances in learning, which have largely occurred outside of psychology, provide a basis for redefining behavior therapy in terms of learning theory. The purpose of this article is to acquaint behavior therapists with these developments.

Alkon (1988), Carew, Hawkins, and Kandel (1983), Gingrich and Byrne (1987), R. D. Hawkins, Carew, and Kandel (1986), R. D. Hawkins and Kandel (1984), and Thompson (1990) demonstrated that the neural basis of learning entails modifying synaptic properties. Just as DNA is a common mechanism of heredity across the phylogetic continuum, so synaptic change seems to be the common mechanism of learning across the phylogenetic continuum.

We recognize empirical and theoretical science as legitimate branches of inquiry. Computational science has more recently been recognized as a legitimate branch of science. It entails formal methods for systematically exploring the consequences of first principles and other specific quantitative axioms and postulates. Computational neuroscience, in part, explores the consequences of learning via synaptic modification in simple first approximations of neural networks. Some modelers emphasize biological fidelity more than others. Hanson and Olson (1990) concluded "... that even models with no relation to the brain beyond the fact that they are built from neuron like elements may provide insight into the brain by showing that a particular function is in principle computable by neurons" (p. 2).

Tryon (1993a, in press) reviewed selected accomplishments of neural network models; therefore, very brief mention will be made here. A sampling of neural network accomplishments includes a) conditioning (Commons, Grossberg, Staddon, 1991; Donegan, Gluck & Thompson, 1989; Gluck & Thompson (1987) Grossberg & Levine, 1987; Grossberg & Schmajuk, 1987, 1989; R. D. Hawkins, 1989; Kehoe, 1988; Klopf, 1988; Sutton & Barto, 1981); b) memory (Hopfield, 1982; Hopfield & Tank, 1987; Kohonen, 1984; c) facial perception (Sejnowski, Lawrence, & Golomb, 1991); d) object detection, including illusions based on figure-ground relationships (Finkel & Sajda, 1992, 1994); e) cognition, including learning to diagnose medical disorders from symptoms (Gluck & Bower, 1988a,b, 1990) and to discriminate edible from poisonous mushrooms (Carpenter, Grossberg, & Reynolds, 1991); f) letter and word perception (Grossberg & Stone, 1986; McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982); and g) learning the past tense of English verbs (Rumelhart & McClelland, 1986) and to pronounce English words by listening to informal child speech (Sejnowski & Rosenberg, 1987). All of these neural network computer simulations gradually acquire their skills through repeated experience that modifies synaptic weights according to a *learning function*. They demonstrate that *learning* is fundamental to all aspects of psychology (e.g., perception, memory, cognition, and behavior).

Many varieties of connectionist neural networks exist, but they share a few fundamental properties. They entail parallel distributed processing by a network of interconnected nodes (neurons) whose synaptic (connection) weights change systematically as a function of experience according to a mathematical learning function. I refer collectively to this approach as neural network learning theory (NNLT). Next, it is shown that NNLT is consistent with important behavioral and cognitive values.

## Theoretical Values

True theoretical synthesis only occurs when important values of opposing theories are embodied in a third theory. The following sections demonstrate that NNLT (connectionist neural networks) is highly compatible with important behavioral and cognitive values and is therefore a synthetic perspective capable of unifying both intellectual traditions of behavior therapy and psychology generally. Compatibility is discussed in terms of properties that are desired to be absent as well as present.

### Behavioral Values

*Absence of:*

*Homunculus.* Skinner (1977, 1989) criticized cognitive psychology for creating a hypothetical inner person or surrogate who processes information and controls the larger person's behavior. He argued that such theories redescribe, rather than explain, behavior because the factors controlling the inner person's behavior are never taken into account. Behaviorists consistently emphasized the importance of avoiding "inner man" explanations.

Neural networks do not have a central processing unit (CPU) that engages in rational choices subsequent to symbol manipulation in accordance with rules, syntax, and grammar. Rather, local changes in synaptic strength across a neural network governed by a mathematical learning function account for the psychological processes mediating environment-behavior relationships. Skinner long maintained that experience changes the organism and believed that neuroscience would eventually explain the physical basis for these changes. Connectionist neural networks constitute great progress in this regard.

*Copy theory of perception.* Skinner (1977, 1989) took exception to the copy theory of perception; he argued that such a theory must then explain how the copy is perceived. Failing to do so begs the initial question of how events are perceived. Neural networks avoid the copy theory of perception. Finkel and Sajda (1992, 1994) simulated object perception using a 128 by 128 pixel "retina" plus 10 neural network layers corresponding to higher levels of visual processing. Their neural network system is capable of perceiving the same visual illusions that people see.

*Rules.* Much of complex human behavior is said to be rule governed. However, Skinner (1977) argued that "Rules are widely used as mental surrogates of behavior . . ." (p. 8). Neural networks frequently give rise to complex behavior that appears to be rule governed without following if-then rules of any kind. Allan (1993) reviewed studies of human contingency judgments and concluded that new associative (connectionist) models better account for the data than do rule-based models.

*Presence of:*

In addition to not having the above mentioned characteristics, for which behaviorists have criticized cognitive psychology, neural networks possess positive qualities that behaviorism has long valued.

*Experience changes the organism.* Skinner (1989) argued that experience changes the organism rather than that the organism stores information. Neural networks are consistent with Skinner's perspective in that synaptic weights change in response to experience. It is the pattern of synaptic weights across the network that gives rise to the complex behaviors that set the occasion for human investigators to infer cognitive rules.

*Determinism.* Behaviorists since J. B. Watson have uniformly advocated the study of behavior as a natural science characterized by deterministic laws. Although Skinner's concept of operants differed from respondents in that the organism was "free" to respond, he and others demonstrated that such choice was a lawful function of environmental variables. Many neural networks use deterministic learning functions to modify synaptic weights as a result of experience. Modeling such events on digital computers brings every aspect of neural network growth and development under scientific study.

*Explicit learning rule.* Learning is traditionally inferred from observed behavior. Operant psychologists refer to behavior rather than learning to avoid this inference. Reinforcement was substituted for learning because it also refers to systematic changes in behavior but is defined by procedures used to alter the probability of a response. Unfortunately, no universally accepted explanation of why a reinforcer is reinforcing has emerged. Neural networks answer this question by using one or another mathematical equation for altering synaptic weights in response to experience. This approach elevates learning to the same hard operational definition basis as all other terms used by behaviorists. It further explains empirical behavior-environment relationships in a parsimonious and biologically relevant manner.

*Explains operant conditioning.* Skinner explained behavior in the same way that Darwin (1950) explained the origin of species: through variation and natural selection (cf., Tryon, 1993b). A second similarity shared with Darwin is that Skinner's functional explanations met the same general lack of acceptance as did Darwin's functional explanations (Alessi, 1992; Bowler, 1983; Catania, 1978, 1987). Not until more than 75 years after the publication of *The Origin of Species* when population genetics provided a plausible proximal mechanism for how selected variations could be retained, was Darwin's evolutionary theory widely endorsed by the scientific community. Neural networks provide a plausible proximal causal mechanism for how behaviors can be selected and retained, thereby setting the occasion for much wider acceptance of Skinner's explanations (cf., Donahoe, Burgos, & Palmer, 1993; Donahoe & Palmer, 1989; Palmer & Donahoe, 1992).

## Cognitive Values

*Presence of:*

Neural networks are unquestionably consistent with cognitive values because they were developed by persons interested in simulating cognitive processes from a brain perspective called cognitive neuroscience. Although no further elaboration is necessary to support this point, the following sections illustrate some of the more important issues.

*Learning entails representation.* A primary premise held by cognitive psychologists is that organisms respond to a representation of external events, not to the events themselves. Representation in a connectionist system is accomplished through a distributed pattern of synaptic weights across the entire network. Learning changes synaptic weights as a result of experience and, consequently, changes the network's representation of these events. The full importance of representation derives from the fact that neural networks can learn only what they can represent, but they can potentially learn everything that they can represent.

*Perception.* Cognitivists have long insisted that perception is an active process. Neural networks illustrate the active nature of perception. Finkel and Sajda (1992, 1994) simulate object detection using a 10-layer neural network; each layer contributes differentially to the final perception, as is the case in real biological systems.

*Memory.* The study of memory has a long tradition in cognitive psychology. Hopfield's (1982) demonstration that multiple memories can be retained by the same neural network and that the full memory can be extracted using only a partial stimulus was a major theoretical contribution to cognitive psychology.

*Cognition.* The ability of neural networks to diagnose medical disorders (Gluck & Bower, 1988a,b, 1990) and to discriminate edible from poisonous mushrooms (Carpenter, Grossberg, & Reynolds, 1991) are clear instances of higher cognitive processing. The majority of neural network accomplishments entail cognition.

*Language.* Cognitive psychologists have long valued the importance of language. The ability of neural networks to perceive letters and words (Grossberg & Stone, 1986; McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982), to learn the past tense of English verbs (Rumelhart & McClelland, 1986), and to learn to pronounce English words, on their own, by listening to informal child speech (Sejnowski & Rosenberg, 1987) makes them an integral part of cognitive psychology.

*Absence of:*

Neural networks are attractive to cognitive psychologists partly because of features they do not share with behaviorism.

*Black box.* Behaviorism has repeatedly been faulted for restricting inquiry to environment-behavior relationships and avoiding theoretical analysis of mediational phenomena. Neural networks directly address the question of mediation. They move well beyond the conceptual nervous system explanations criticized by behaviorists by specifying mathematical and computer simulations capable of simulating many important psychological and behavioral phenomena.

*Primary reliance on animal models.* Behaviorists have been criticized for their heavy emphasis on the laboratory study of animal behavior. Extensions of behavioral explanations to human behavior are not widely accepted, in part, because they are considered to be only partially relevant. However, the same neural network concepts/principles used to explain conditioning in animals are used to explain higher human intellectual functions with equal relevance. This explanatory freedom to move up and down the phylogenetic continuum is itself a major theoretical synthesis.

## Conclusions

1) Because neural networks embrace the positive values of both sides and avoid the negative elements each side reports to be characteristic of the other, there is no further merit to the cognitive versus behavioral debate. We can even discard our hyphenated cognitive behavior descriptor. Behavior therapy can just be known to be based on a class of biologically inspired learning mechanisms from which the full spectrum of psychological processes and behavior emerge.

2) Because NNLT pertains equally well across the entire phylogenetic continuum, students of human and animal behavior will, for the first time, share a common vocabulary and set of fundamental principles. This will increase the human relevance of animal studies and will allow theoretical formulations derived in connection with serving human clients to be studied in the animal and computing laboratories.

3) Understanding learning as a process of synaptic modification makes it much clearer how neuroleptic medications, which influence neurotransmitters, can alter psychological states and the behaviors they mediate. Behavior therapists, through learning, and physicians, through medications, both seek to alter synaptic states. Consequently, NNLT provides a theoretical interface between psychologists and biological psychiatry. There are many scientific and professional benefits associated with such a broad intellectual reconciliation.

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# Cognitive Behavioral Group Aggression Management Training in a Children's Psychiatric Hospital

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The patients in the children's unit of C.P.C. Fairfax Hospital in Kirkland, Washington, are predominantly Caucasian males aged 8 to 11, and nearly all are referred by their parents or guardians following threats or acts of aggression toward family or peers. Several have made suicidal threats or attempts. Roughly half of the patients are diagnosed with attention-deficit hyperactivity disorder and/or dysthymia (APA, 1987). A few have been diagnosed with anxiety, psychotic, or other mood disorders. Average length of stay is between 2 and 3 weeks, depending on level of acuity. Because aggressive threats or acts are the predominant target complaint, a cognitive behavioral aggression management program based on multicomponent adult models of treatment for domestic violence and other forms of anger dyscontrol was implemented (Deffenbacher, McNamara, Stark, & Sabadell, 1990; Faulkner, Stoltenberg, Cogen, Nolder, & Shooter, 1992; Saunders, 1989). Such programs typically include interventions such as assertion training, arousal reduction, and social skills training. The treatment components were presented in hour-long groups as "Themes of the Day," six per week, in order to ensure that every patient would receive each component at least once during hospitalization.

## Interventions

*Assertion Training*

Each Monday the treatment theme was assertion training, a skill often deficient among aggressive, depressed, or anxious adults and children, (Bornstein, Bellack, & Hersen, 1977; Faulkner et al., 1992) that is readily modified by behavioral training (Bornstein et al.; Foy, Eisler, & Pinkston, 1975). Assertion is defined here as the ability to express positive and negative feelings, the ability to refuse inappropriate or unreasonable requests, and the ability to make specific, behavioral requests of others (Masters, Burish, Hollon, & Rimm, 1987).

Intervention followed the training model described by Bornstein et al. (1977): The therapist provides verbal feedback to roleplayed conflicts, models the desired behavior, and explains the general principles underlying the desired behavior. As an additional means of conveying the principles of assertion to children, a booklet and didactic presentation entitled "Sharks, Mice, and Bears" (see Polischuk & Collins, 1991) were used to differentiate aggressive, passive, and assertive behavior:

> Sharks go around looking for someone to pick on. Usually, sharks like to pick on people who are weaker than they are. Mice are afraid to speak up for themselves. They hope and pray that the problem will go away, but they don't do anything about it. Bears tell people how they feel: "It makes me mad when you do that." Bears say no to unreasonable requests. Bears ask for what they want. (p. 41)

In addition to these descriptions, the booklet contains "quizzes" that enabled the children to identify their own behavior as assertive, passive, or aggressive.

Maladaptive cognitions have been demonstrated to play a significant role in unassertive behavior (Hammen, Jacobs, Mayol, & Cochran, 1980) and are amenable to rational restructuring in adults (Hamberger & Lohr, 1980). Thus, the intervention also outlined some of the basic assumptions (Beck & Freeman, 1990) underlying these behavior patterns.

*Social Skills Training*

Social skills training was Tuesday's theme. Aggressive adults and children have been found to lack the necessary skills for prosocial behavior (Faulkner et al., 1992; Frederiksen, Jenkins, Foy, & Eisler, 1976; Stern & Fodor, 1989). Guevremont and Foster (1993) demonstrated that social skills training could at least temporarily improve the prosocial behavior of aggressive boys.

For our social skills component, each patient was taught social cues, such as proper tone of voice, eye contact, and body positioning (Frederiksen et al., 1976). The therapist roleplayed typical social opportunities, such as meeting a recently admitted patient