in Comparison and Contrast, ed. Rene Dirven and Ralf Pörings, 533–54. Berlin: Mouton de Gruyter.

Kovecses, Zoltan. 2002. *Metaphor: A Practical Introduction*. Oxford: Oxford University Press.

Lakoff, George. 1987. *Women, Fire and Dangerous Things: What Categories Reveal About the Mind*. Chicago and London: University of Chicago Press.

———. 1993. "The contemporary theory of metaphor." In *Metaphor and Thought* 2d ed. Ed. Andrew Ortony, 202–51. Cambridge: Cambridge University Press.

Lakoff, George, and Mark Johnson. 1980. *Metaphors We Live By*. Chicago: University of Chicago Press.

Littlemore, Jeannette, and Graham Low. 2006. *Figurative Thinking and Foreign Language Learning*. Basingstoke, UK: Palgrave MacMillan.

Low, Graham. 1999. "Validating metaphor research projects." In *Researching and Applying Metaphor*, ed. Lynne Cameron and Graham Low, 48–65. Cambridge: Cambridge University Press.

———. 2003. "Validating models in applied linguistics." *Metaphor and Symbol* **18**.4: 239–54.

Ramachandran, V. S., and E. M. Hubbard. 2001. "Synaesthesia – a window into perception, thought and language." *Journal of Consciousness Studies* **8**.12: 3–34.

Stefanowitsch, Anatol, and Stefan Gries, eds. 2006. *Corpus-based Approaches to Metaphor and Metonymy*. Berlin: Mouton de Gruyter.

CONDUIT METAPHOR

The conduit metaphor (Reddy [1979] 1993) models **COMMUNICATION** as a process in which the speaker *puts* information *into* words and *gets it across* to a receiver, who tries to *find* the meaning *in* the words. Words are understood as containers, meanings as objects that can be put into words. Reddy was concerned with the biasing influence this model has on our thinking about communication.

– Jörg Zinken

WORK CITED

Reddy, Michael J. [1979] 1993. "The conduit metaphor: A case of frame conflict in our language about language." In *Metaphor and Thought*, ed. A. Ortony, 164–201. Cambridge: Cambridge University Press.

CONNECTIONISM AND GRAMMAR

Connectionist approaches to language employ artificial neural networks to model psycholinguistic phenomena (see CONNECTIONIST MODELS, LANGUAGE STRUCTURE, AND REPRESENTATION). Although a few connectionist models have been used to directly implement traditional types of grammar (e.g., Fanty 1986), most aim to offer new ways of capturing key properties of grammar, such as **CONSTITUENT STRUCTURE** and recursion (see RECURSION, ITERATION, AND METAREPRESENTATION). In particular, the latter models seek to demonstrate how important aspects of grammar may emerge through learning, rather than being built into the language system. This entry, therefore, focuses on the radical connectionist models as they promise to provide new ways of thinking about grammar and, as such, potentially could provide the most substantial contribution to the language sciences.

Words in sentences are not merely strung together as beads on a string but are combined in a hierarchical fashion. Grammars capture this by specifying a set of constraints on the way that words are put together to form different types of constituents, such as noun phrases and verb phrases, as well as the way these phrases may be combined to produce well-formed sentences. Connectionist models have begun to show how constituent structure may be learned from the input. J. L. Elman (1990) trained a simple recurrent network (which has a copy-back loop providing it with a memory for past inputs) on a small context-free grammar and was able to show that the network could acquire aspects of constituent structure. In related work, M. H. Christiansen and N. Chater (1994) demonstrated that this kind of model is capable of generalizing to novel syntactic constructions involving *long-distance dependencies* across constituents, suggesting that it is able to exploit linguistic regularities that are defined across constituents. A subsequent model by D. L. T. Rohde (2002) has further shown that constituent structure can be learned from more natural language-like input than that used by previous models, indicating that this approach may scale up well to deal with full-blown language.

The notion of constituency that emerges in these models is not the same as what is found in standard models of grammar. Rather, connectionist models suggest a more context-sensitive notion of constituency, dividing words and phrases into clusters without categorical boundaries and treating them differently depending on the linguistic context in which they occur. For example, Elman's (1990) model was able to learn context-sensitive animacy constraints from word co-occurrence information, thus allowing it to distinguish semantically meaningful sentences (e.g., *The boy broke the plate*) from nonsensical ones (e.g., *The plate broke the boy*).

The generative power of grammars derives from recursion, the notion that constituents can be embedded within one another and even within themselves. The model by Elman (1991) was perhaps the first to demonstrate the acquisition of a limited ability to process recursive structure in the form of right-branching relative clauses (e.g., *The cat chased the mouse that bit the dog*), as well as center-embedded constructions (e.g., *The mouse that the cat chased bit the dog*). Christiansen and Chater (1994), as well as Rohde (2002), extended this initial work by incorporating several additional types of recursive structure, including sentential complements (e.g., *Mary thinks that John says that …*), possessive genitives (e.g., *John's brother's friend …*), and prepositional phrases (e.g., *The house on the hill near the lake …*). Additionally, Christiansen and Chater (1999) demonstrated that the performance of connectionist models closely match human data from German and Dutch that relates to complex sentences involving recursive center embeddings (with the following dependency relationship between nouns and verbs $N_1\ N_2\ N_3\ V_3\ V_2\ V_1$) and cross-serial dependencies ($N_1\ N_2\ N_3\ V_1\ V_2\ V_3$), respectively. Specifically, people find doubly center-embedded constructions in German much harder to process than comparable levels of cross-serial dependency embedding in Dutch (controlling for semantic factors across the two languages), and this pattern of processing difficulty was mirrored closely by the model. As with the connectionist notion of constituency, the recursive abilities of connectionist models deviate from standard conceptions of recursion. Specifically, connectionist models are unable to accommodate unlimited recursion; it is important to note, however, that they are able to capture recursion at the level of human abilities, as evidenced by **PSYCHOLINGUISTIC** experimentation.

Connectionist approaches to grammar are still very much in their infancy and currently do not have the kind of coverage and grammatical sophistication as seen in more traditional computational models of syntax. Moreover, the question remains as to whether the initial encouraging results described here can be scaled up to deal with the full complexities of real language in a psychologically realistic way. If successful, however, then the conception of grammar may need to be radically rethought, including notions of constituency and recursion. Already, connectionist models have suggested that the idea of an infinite linguistic **COMPETENCE,** as typically prescribed by **GENERATIVE GRAMMAR,** may not be required for capturing human language **PERFORMANCE**. In this regard, the kind of grammatical framework hinted at by connectionist models more closely resemble those of **CONSTRUCTION GRAMMARS** and the **USAGE-BASED THEORY** of language than the traditional generative grammar approaches. Whatever the future outcome of the connectionist approach to grammar may be, it is likely to stimulate much debate over the nature of grammar and language itself – as it has done in the past – and this, in the long run, may be where connectionism will have the largest impact on the way we think about grammar within the language sciences.

– Morten H. Christiansen

WORKS CITED AND SUGGESTIONS FOR FURTHER READING

Christiansen, M. H., and N. Chater. 1994. "Generalization and connectionist language learning." *Mind and Language* **9**: 273–87.

———. 1999. "Toward a connectionist model of recursion in human linguistic performance." *Cognitive Science* **23**: 157–205.

———. 1990. "Finding structure in time." *Cognitive Science* **14**: 179–211.

Elman, J. L.. 1991. "Distributed representation, simple recurrent networks, and grammatical structure." *Machine Learning* **7**: 195–225.

Fanty, M. A. 1986. "Context-free parsing with connectionist networks." In *Neural Networks for Computing*, ed. J. S. Denker, 140–45. New York: American Institute of Physics.

Onnis, L., M. H. Christiansen, and N. Chater. 2005. "Cognitive science: Connectionist models of human language processing." In *Encyclopedia of Language and Linguistics,* ed. K. Brown. Oxford: Elsevier. This review article provides a more detailed treatment of the issues discussed here.

Rohde, D. L. T. 2002. "A connectionist model of sentence comprehension and production." Ph.D. diss., Carnegie Mellon University, Department of Computer Science, Pittsburgh, PA.

Rohde, D. L. T., and D. C. Plaut. 2003. "Connectionist models of language processing." *Cognitive studies* **10**: 10–28. Another review of connectionist models of language.

CONNECTIONISM, LANGUAGE SCIENCE, AND MEANING

Connectionism, or parallel distributed processing, is a general term for a set of particular cognitive architectures. With some variations, these architectures model mental processes on a shared set of constituents and operations, drawn from neurobiology. The constituents are parallel to neurons, and the operations are parallel to the firing of neurons. However, connectionist models are not strictly neurobiological and may be implemented in various materials (e.g., computers). More exactly, a connectionist architecture has nodes as its basic constituents. These nodes are linked to one another, forming circuits. The nodes may have different degrees of activation, and they receive activation from other nodes in the circuit. When a node is activated – in some models, when it reaches a particular level of activation, a threshold – it fires, transmitting its activation to subsequent nodes in the circuit.

The individual connections among nodes are commonly understood to have different degrees of strength. Strength is typically a multiplicative relation, such that the activation of the firing or input node is multiplied by the connection strength to yield the amount of activation transmitted to the recipient node (e.g., a node firing at level 1 delivers a level of activation to a second node of .5 if the strength of the connection between the nodes is .5). These connection strengths may be altered by activation sequences (e.g., in many models, when nodes activate together, the strength of their connection increases). The connections may be excitatory or inhibitory – that is, a first node my increase or decrease the activation of a second node. Connectionist circuits or *neural networks* commonly have a set of input nodes, a set of output nodes, and layers of "hidden" nodes. Connectionist models also incorporate some way that errors may be detected and corrected. In a connectionist model, correction is a matter of readjusting connection strengths among the nodes in the circuit.

Connectionist modeling has two broad purposes. One relates to artificial intelligence. The other relates to actual human cognition. Insofar as connectionist models are designed to explain human cognition, the models are constrained by properties of human behavior. Take, for example, a connectionist model of plural formation in English. If a connectionist is merely setting out to create a program that generates plurals, he or she does not need to worry about the precise sorts of errors actual human beings make with plurals, the way plural usage develops in childhood, and so on. However, a connectionist who is modeling actual human language will wish to design a system that produces the same curve of correct plurals and errors that we find among real people.

Connectionism and Neuroscience

The artificial intelligence value of connectionism seems clear. But with respect to human language, one might ask – why bother with connectionist modeling at all? Why don't we simply do neuroscience? After all, connectionism takes up the basic principles of neurobiology – neuronal units, firing thresholds, circuits. However, it tends to eschew the fine-grained, empirically based assignment of specialized neuronal or regional functions. Moreover, it simply leaves out such important components of neurobiology as neurochemistry.

Certainly, connectionist modeling of human cognitive architecture cannot replace neuroscience. Moreover, it does seem clear that such modeling should follow the basic principles of neuroscience (e.g., in modeling human language, it should not posit processes that have no correlate in the brain). However,