



A psycholinguistically and neurolinguistically plausible system-level model of natural-language syntax processing

Alan H. Bond*

Computer Science Department, California Institute of Technology, 1201 California Boulevard Mailstop 256-80, Pasadena, CA 91125, USA

Available online 18 December 2004

Abstract

We describe a psycholinguistically and neurolinguistically plausible model of natural-language processing by the human brain. This model is based on the work of Gerard Kempen and coworkers at Leiden and Nijmegen who have developed computational models of language generation and of language recognition. We show how to use our own brain modeling approach to develop a neurolinguistically plausible model based on the Kempen psycholinguistic model. Our model is implemented as a set of inter-communicating brain modules that run in parallel. These brain modules have the same structure and control regime as other nonlinguistic brain modules. They approximately correspond to Broca's and temporal lobe areas.

© 2004 Elsevier B.V. All rights reserved.

Keywords: Psycholinguistics; Lexical; Unification; Agrammatism

1. Introduction

Purpose: The purpose of the present research is to define a brain model based on Kempen's psycholinguistic theory [10,12], using our own logical system approach to brain modeling [1–6].

*Tel.: +1 626 3956430; fax: +1 626 7924257.

E-mail address: bond@cs.caltech.edu (A.H. Bond).

The work of Gerard Kempen: Gerard Kempen [9,11] has developed an approach to language processing which is psycholinguistically plausible. He and his coworkers have specified and implemented both language generation [8,13] and language recognition [14] systems on computers.

2. Our general brain modeling approach

We have developed a system-level modeling approach to the brain [4–6].

Modules: A system-level brain model is a set of parallel modules with fixed interconnectivity similar to the cortex and where each module corresponds to a brain area and processes only certain kinds of data specific to that module.

Data items and their storage and transmission: We view all data streams and storage as made up of discrete data items which we call *descriptions*. We represent each data item by a logical literal which indicates the meaning of the information contained in the data item. An example data item is `position(adam, 300, 200, 0)` which might mean that the perceived position of a given other agent, identified by the name “adam”, is given by (x, y, z) coordinates (300,200,0). In order to allow for ramping up and attenuation effects, we give every data item an associated strength, which is a real number. Stored data items are ramped up by incoming identical or related data items and they also attenuate with time, at rates characteristic of the module.

Processing within a module: We represent the processing within a module by a set of left-to-right rules which are executed in parallel. A rule matches to incoming transmitted data items and to locally stored data items and generates results which are data items which may be stored locally or transmitted. Rule patterns also have weights and the strength of a rule instance is the product of the matching data item weights and the rule weights, multiplied by an overall rule weight.

A rule may do some computation which we represent by arithmetic. This should not be more complex than can be expected of a neural net. The results are then filtered competitively depending on the data type. Typically, only the one strongest rule instance is allowed to “express itself”, by sending its constructed data items to other modules and/or to be stored locally. In some cases however all the computed data is allowed through.

Uniform process: The uniform process of the cortex is then the mechanism for storage and transmission of data and the mechanism for execution of rules.

Perception-action hierarchy: Modules are organized as a *perception-action hierarchy*, which is an abstraction hierarchy with a fixed number of levels of abstraction.

The perception hierarchy receives sensory data items at the bottom and derives higher level descriptions to form a percept. The action hierarchy generates more and more detailed descriptions of action, that is, it elaborates the plan to the point where motor actions are generated at the bottom of the action hierarchy.

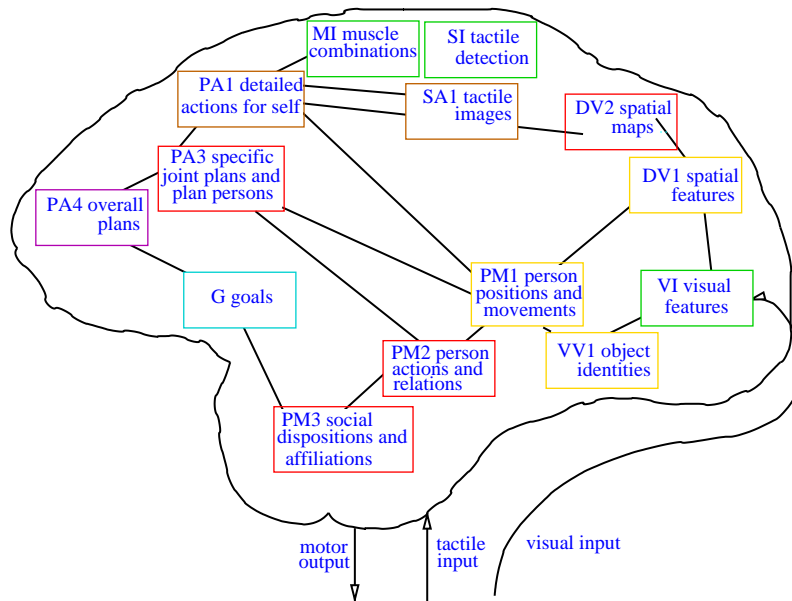


Fig. 1. Our system model shown in correspondence with the neocortex.

Fig. 1 shows the correspondence of our initial model to the primate neocortex. Note that the goal module corresponds to an area on the inner (medial) surface, namely the anterior cingulate.

3. Kempen's model of grammar

Overview of sentence recognition: The sentence is read in, incrementally, word by word and a structure description is constructed incrementally and dynamically, being updated after each word.

The lexicon: The approach is lexicalist, in that there is very little grammar that is not derived from the lexicon. Words are held as *lexical frames*, which are four-tiered unordered trees which are “mobiles”, i.e., there is no ordering among branches. Fig. 2 depicts some frames. They have variables, such as np, dp, pp and s, at certain places which can be linked to form structure descriptions for sentences.

Grammatical features: Each variable has an associated set of features. For example, a noun phrase, type np, can have a set of feature values composed of subsets of the following feature sets: person—{first, second, third}, number—{singular, plural}, case—{nominative, accusative}. The set of features is called a *matrix*. A particular instance of a noun phrase might have, e.g., [case = {nominative, accusative}, number = {singular}, person = {third, first}]. There can also be features shared between the root and frame components.

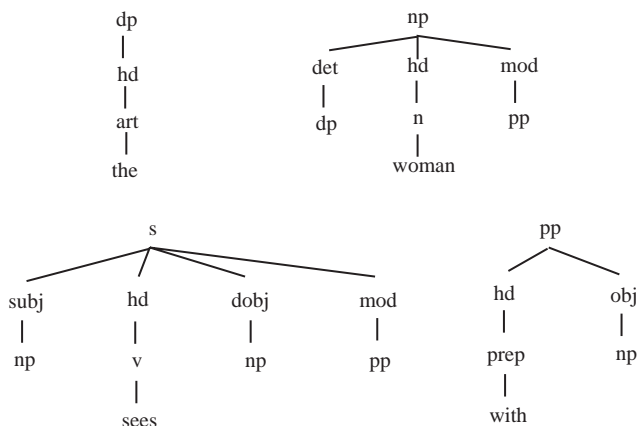


Fig. 2. Lexical frames.

Unification: The unification process used in this theory differs from head-driven phrase structure grammar and lexical-functional grammar in being nonrecursive and involving only feature unification. Two lexical frames are combined by unifying a variable from one frame with a variable from the other frame. Unification is an agreement check between two nodes that become unified. For example, to unify [case = {nominative, accusative}, number = {singular}, person = {third, first}] with [person = {first, second, third}, case = {nominative}], we proceed as follows [12]:

1. For each shared feature type, find the intersection of possible values: [person = {first, third}, case = {nominative}].
2. If some shared feature type has no intersection, unification fails.
3. For nonshared features, keep the same: [number = {singular}].
4. Form new matrix from the union of results of 1 and 3: [case = {nominative}, number = {singular}, person = {third, first}].

Word-order check: There is a word ordering process, and there must be consistency between the input order of words and their position in the structure description.

U-space: U-space is where the structure description is formed. At each moment, U-space consists of a set of lexical frames. Lexical frames are linked by u-links which represent unifications of variables present in these frames. Each u-link has an instantaneous strength and each lexical frame has an activation value, which are real numbers.

Dynamic creation of structure descriptions: In a language recognition regime:

- (i) a new input word generates a lexical frame, or frames, which is (are) added to the U-space. Its initial activation value is taken from the lexicon.
- (ii) U-links are created from the root node(s) of the new lexical frame to all existing matching foot nodes and from all existing and matching root nodes to the foot nodes of the newly entered lexical frame. The initial strength of these u-links is 0.

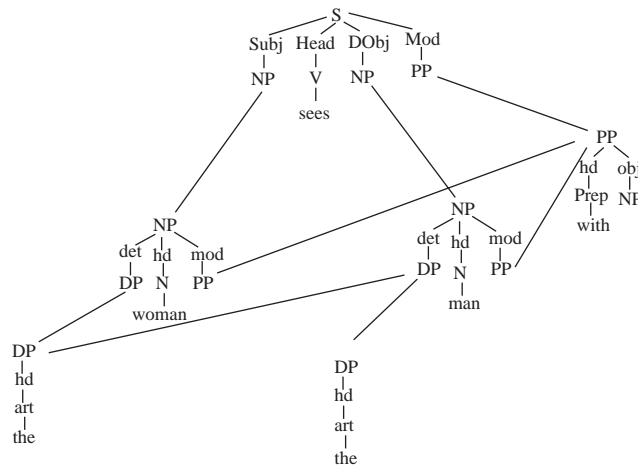


Fig. 3. Step during construction of structure description.

- (iii) Then the activation values of all frames are decremented.
- (iv) Then the strength values of all u-links are updated according to a competitive inhibition process and also as a result of the application of certain global integrity conditions.

Competitive inhibition: U-links overlapping at the same node will inhibit each other by an amount linearly related to their current strengths and to the activation values of the nodes involved.

An example of sentence recognition: An example is given in the Vosse and Kempen (V–K) paper [14]: “The woman sees the man with the binoculars”. Fig. 3 shows one step during construction of the structure description, at the point where “The woman sees the man with” has been received.

Competing u-links can be seen. By inhibition, the process will eventually settle to have unique u-links, which gives the structure description of the input sentence.

Vosse and Kempen’s results: The performance of their model on 30 sample sentences, taken together, exhibits a large portion of reported psycholinguistic phenomena, including garden path sentences, nesting of clauses, word ambiguities and so on.

Agrammatism: Vosse and Kempen went on to apply their system to the clinical condition agrammatism. They got a good fit to performance using a set of nine sentence types developed by Caplan [7] for evaluating agrammatic patients.

4. Our grammatical model for the brain

We can now discuss how we formulated the Vosse–Kempen psycholinguistic model in terms of our brain model.

Basically, the decrementation of activation weight and the incrementation of u-link strength can be modeled by mechanisms already provided in the brain model architecture. Then we extended the brain model to provide inhibition of competing overlapping structures:

1. Activation decrements will occur by attenuation of the word data item, and the continuous reconstruction of the evoked lexicon item.
2. The spontaneous incrementation of u-links will follow from the ramping up of strength of the lexical frame data items in the u-space module. For this to work, we needed to make the effect of u-link strength depend on the strengths of the lexical frames it unifies.

As regards inhibition of overlapping u-links, this could be made a general property of the brain model and the data items used. At the moment, each type of data item has a specification of how it is to be updated. It is possible to specify uniqueness of data items so that only one of a given type can occur in the store at any one time. If a new item enters it simply replaces the previous value. It is also possible to specify that there can be multiple items of the same data type. The kind of competitive competition needed here would be a generalization of the model. There could be multiple copies but they could compete over a number of cycles to eventually leave one item only.

Thus, we will now look at how to extend our data item concept to provide this kind of uniqueness and competition as a general property of the working of the brain model. There are certain properties of perception in general; each perceived object has one and only one interpretation.

Our Approach: We first developed straightforward representations as descriptions.

We concluded that u-links are not neurally plausible as data items. We instead decided to represent the same information in a new kind of description which we called a *unified lexical frame*. Thus, the store where the sentence structure description is constructed will contain only unified lexical frames. We used the property of our brain model that it *continuously reconstructs* data items. We also did not think that a global integrity enforcement process was neurally plausible either. To achieve the same computation as V–K, a brain model rule continually, every brain model cycle, reconstructs all the different possible unified lexical frames. Because of this, the data items representing unified lexical frames need to carry more information to allow the different integrity requirements to be implemented as reconstruction actions. Thus, we used two main rules: (1) create lexical frame from word: word → lexical_frame and (2) unify lexical frame to create u-link: lexical_frame_1 and lexical_frame_2 → unified_lexical_frame_12.

As regards the issue of *learnability* of grammar from positive, i.e. grammatical, instances of sentences, we will need to make the inhibition/exclusion principle a general principle independent of the particular grammar. This principle corresponds to the idea of uniqueness of a match or association.

Thus, to summarize, the store corresponding to U-space will contain only lexical frames and unified lexical frames and this brain module will contain a set of parallel rules which act every cycle and which elaborate and reconstruct the unified lexical

frames each cycle. This is all the mechanism that we will have, there will be no separate u-links and there will be no separate global integrity enforcement process. All of these mechanisms are achieved by rules and unified lexical frames.

Note that our brain model already does attenuation of activation values. Every lexical frame will decay with time because the sensed word will decay with time.

The nominal rate is 20 ms per cycle. Lexical frames will be renewed every 20 ms and therefore unification links also since they are part of unified lexical frames. At a normal speaking rate of 140 words per min and 7 words per sentence this is 20 sentences per min, giving 3 s per sentence and 400 ms per word. Thus, there will be

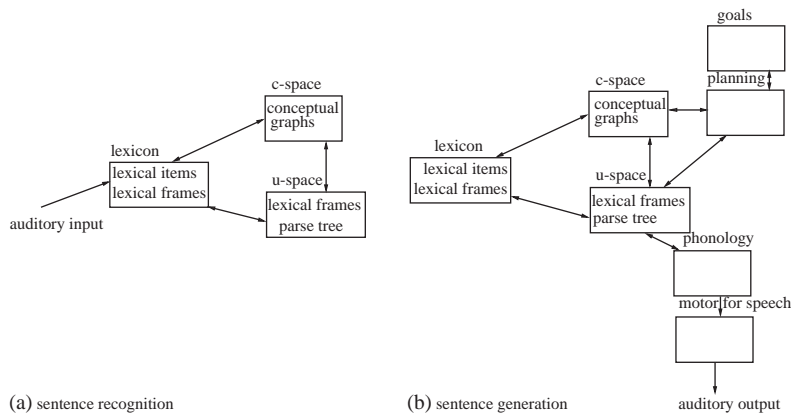


Fig. 4. Processes organized as concurrent modules.

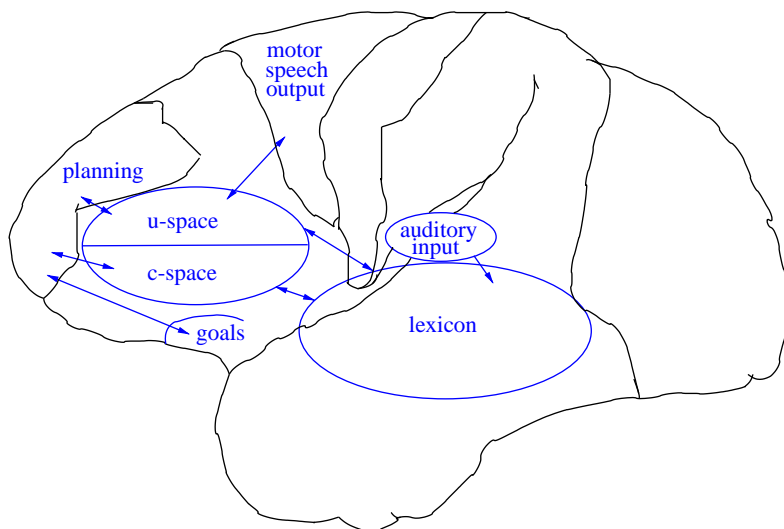


Fig. 5. Brain areas corresponding to concurrent modules.

about 20 brain cycles for each new word, and therefore 20 cycles of reconstruction of the structure description in each increment.

In Fig. 4, we speculate that the processes are organized as modules which run in parallel, and in Fig. 5, how it would correspond to areas of the brain.

5. Conclusion

We were able to develop a system level brain model of sentence recognition based on the Vosse–Kempen psycholinguistic model. Several existing brain model mechanisms could be used to represent mechanisms occurring in their model. Our continuous construction execution regime provided a natural mechanism for sentence recognition. We added one new mechanism, namely the competitive inhibition of data items with specified overlap. We see this as a general brain mechanism. Our system is currently able to recognize some of VK's example sentences and we are continuing to develop the model. Our model uses just two modules, corresponding to the lexicon and to U-space and probably to Broca's area and temporal lobe areas. A fuller model would also have a semantic module and input and output phonological modules.

References

- [1] A.H. Bond, A computational architecture for social agents. in: *Proceedings of Intelligent Systems: A Semiotic Perspective, An International Multidisciplinary Conference, National Institute of Standards and Technology, Gaithersburg, Maryland, USA, 20–23, October 1996.*
- [2] A.H. Bond, A system model of the primate neocortex, *Neurocomputing* 26–27 (1999) 617–623.
- [3] A.H. Bond, Describing behavioral states using a system model of the primate brain, *Am. J. Primatol.* 49 (1999) 315–388.
- [4] A.H. Bond, Problem-solving behavior in a system model of the primate neocortex, *Neurocomputing* 44–46C (2002) 735–742.
- [5] A.H. Bond, A computational model for the primate brain based on its functional architecture, *J. Theoret. Biol.* 227 (2004) 81–102.
- [6] A.H. Bond, An information-processing analysis of the functional architecture of the primate neocortex, *J. Theoret. Biol.* 227 (2004) 51–79.
- [7] D. Caplan, C. Baker, F. Dehaut, Syntactic determinants of sentence comprehension in aphasia, *Cognition* 21 (1985) 117–175.
- [8] Carel Van Wijk, G. Kempen, A dual system for producing self-repairs in spontaneous speech: evidence from experimentally elicited corrections, *Cognitive Psychol.* 19 (1987) 403–440.
- [9] G. Kempen, Conceptualizing and formulating in sentence production, in: S. Rosenberg (Ed.), *Sentence Production: Developments in Research and Theory*, Lawrence Erlbaum Associates, Hillsdale, NJ, 1977, pp. 259–274.
- [10] G. Kempen, Sentence construction by a psychologically plausible formulator, in: R.N. Campbell, P.T. Smith (Eds.), *Recent Advances in the Psychology of Language: Formal and Experimental Approaches*, Plenum Press, New York, 1978, pp. 103–123.
- [11] G. Kempen, A framework for incremental syntactic tree formation, in: *Proceedings of the 1987 International Joint Conference on Artificial Intelligence, 1987*, pp. 655–660.
- [12] G. Kempen, *Performance Grammars, 2000*, unpublished book manuscript.

- [13] K. De Smedt, G. Kempen, Segment grammar: a formalism for incremental sentence generation, in: C.L. Paris, W.R. Swartout, W.C. Mann (Eds.), *Natural Generation in Artificial Intelligence and Computational Linguistics*, Kluwer, Dordrecht, 1991, pp. 329–349.
- [14] T. Vosse, G. Kempen, Syntactic structure assembly in human parsing: a computational model based on competitive inhibition and a lexicalist grammar, *Cognition* 75 (2000) 105–143.



Alan H. Bond was born in England and received a Ph.D. degree in theoretical physics in 1966 from Imperial College of Science and Technology, University of London. From 1966 to 1969, he was on the faculty of the Computer Science Department at Carnegie-Mellon University, Pittsburgh. During the period 1969 to 1984, he was on the faculty of the Computer Science Department at Queen Mary College, London University, where he founded and directed the Artificial Intelligence and Robotics Laboratory. From 1985 to 1992, he lead research in applied artificial intelligence at the University of California, Los Angeles. He has published research in autonomous robotics, multiagent systems and parallel computer architectures. Since 1996, he has been a Senior Scientist and Lecturer at

California Institute of Technology. His main research interest concerns the system modeling of the primate brain.