A NEURAL NETWORK MODEL FOR THE REPRESENTATION OF NATURAL LANGUAGE: THE CASE OF HOMONYMY

ELENI KOUTSOMITOPOULOU*

LexisNexis UK, Information Extraction and Indexing, London, UK
Georgetown University, Washington D.C., USA, Computational Linguistics
E-mail: eleni.koutsomitopoulou@lexisnexis.com

This study focuses on a biologically faithful neural network simulation, the Cognitive Linguistic Adaptive Resonant Network (CLAR-NET) model of online and real-time associations among concepts with input from everyday English. Specifically, conceptual linguistic associations are now (Loritz 1999) analyzed as dynamic resonant patterns represented in this study in terms of neuronal activation. The CLAR-NET model extends this line of research to various linguistic phenomena in the realm of conceptual analysis: homonymy, polysemy, constructional polysemy (Goldberg 1995), ambiguity, reseamblance and primary metaphor (Grady et al. 1996), neologism, contextual coreference, subject-object control, event-structure metaphor (Lakoff 1980), negation. Investigating the representation of natural language in biologically faithful neural networks is a prelude to a new line of research and holds implications for language learning, neurolinguistics, metaphor theory, information retrieval, knowledge engineering, case-based reasoning, knowledge-based machine translation systems and related ontologies.

1. Background

1.1. *Why a Neural Network approach for Natural Language?*

Formal representation methods give good context-free analyses of noise-free linguistic input by enforcing an abstraction away from the actual properties of real-time natural language (NL). On the other hand, semantic fuzziness and the realities of the linguistic and discourse context are systematically ignored.

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Natural language is a human neurocognitive phenomenon and as such it can be best represented in a biologically faithful neural network model.

1.2. *What's new about this Neural Network model for NL?*

Most "connectionist" architectures model cerebellar cortex (e.g. Parallel Distributed Processing, PDP). However, language learning primarily occurs in cerebral cortex (Loritz, 1991). Grossberg's early Adaptive Resonance Theory (ART) describes cerebral anatomies and processes. Loritz 1999 first explained a range of phonological, morphological and syntactic NL phenomena within the general ART framework. Koutsomitopoulou 2004 further extended the Adaptive Grammar model (AG, Loritz 1999) to a number of critical semantic linguistic events.

Using lateral inhibition in an ANN model focusing on NL input is a relatively new idea. Even when lateral-inhibition models have been proposed for NL input (as in the PDP model), there is no provision for the general neurobiological faithfulness of the model, which should involve both short-term (STM) and long-term memory (LTM) in computing node activation. Another example of a STM model for word-sense disambiguation that suggests inhibition is that of Cottrell and Small 1983, and Cottrell et al 1988. However, inhibition in these models is only recognized as a necessary part of the disambiguation process which results in selection among particular (often ad hoc) semantic alternatives of simple word-level NL input. Before CLAR-NET there has been no attempt of modelling high level cognitive linguistic tasks where lateral inhibition is a ubiquitous mechanism of a STM and LTM system [a].

2. The CLAR-NET Algorithm

(1) Map input from parser to the network.
(2) Learn input at time t.
(3) Introduce new (phasic) input to the network at time $t+1$.
(4) Until stabilization, compute overall network resonance.

2.1. *Adaptive Resonance Theory and Adaptive Grammar*

CLAR-NET calculates both short-term memory (STM) and long-term memory (LTM) by modeling both excitatory and inhibitory forces (cor-

[a] For more detailed criticism of both PDP and Cottrell's models please refer to the Koutsomitopoulou 2004

responding to neurotransmitter release). Roughly, the former facilitates learning, whereas the helps the network classify (disambiguate) a given input.Equations 1 and 2 below were introduced by Grossberg 1972 for the calculation of SMT and LTM via excitatory and inhibitory parameters:

$$\dot{x}_j = -Ax_j + Bx_i z_{ij} - Cx_k z_{kj} + I \tag{1}$$

$$\dot{z}_{ij} = -Dz_{ij} + Ex_i x_j \tag{2}$$

Parameter A = natural STM decay (forgetting). **Parameter** B = SMT learning rate. **Parameter** C = inhibition rate. **Parameter** D = natural LTM decay. **Parameter** E = LTM learning rate. z_{ij} is the change in the weighted connection between node at site x_j and its excitatory x_i (Hebbian learning). **Parameter** I = type of regulatory exogenous input.

3. Illustrative case: Homonymy

In this paper I briefly present the case of homonymy. For a detailed analysis of this and a range of other linguistic phenomena please refer to Koutsomitopoulou 2004.

Consider the following simple natural language sentences:

(1) The bow of this ribbon has two loops.
(2) I used a new bow for shooting those arrows.
(3) Arrow is a weapon.
(4) John has a weapon.

In sentences 1 and 2, *bow* is homonymous. In 1, *bow* belongs in the domain of *ribbons*, whereas in sentence 2 *bow* belongs in the domain of *arrows*. Sentence 3 is a factoid about *arrows*. In psychological terms, "factoids" are akin to "priming stimuli". After Ss 1-3 have been learned, S4 is presented as a "phasic input" or "probe stimulus" at time *t+1*. We seek to understand how the network responds or "learns" in response to this probe stimulus. The network diagram in figure 1 shows how Ss 1-4 are mapped into the CLAR-NET system. Notice that sentence S1 has two nominal nodes mapped on the network: Ribbon and Bow. Sentence S2 contains Bow and Arrow. Sentence 3 (S3) is the factoid about Arrow as a Weapon. Sentence 4 (S4) presents phasic input at time *t+1*.

3.1. *STM results and LTM effects of the above experiment*

The *Bow* node of S2 bearing the connotations of *arrow* and *weapon* achieves a high activation relative to the activation value of *Bow* node of

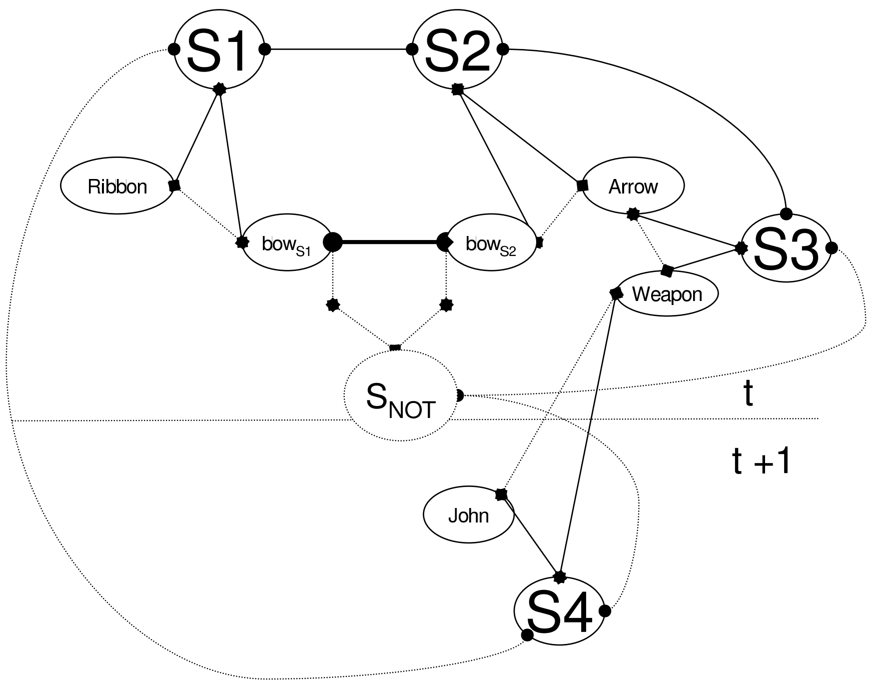

Figure 1. *Bow* homonymy.

S1, because *Bow* node of S2 and *Bow* node of S1 compete in an inhibitory dipole (represented in the network diagram by the S_{NOT} node).This means that the reading of the homonym *bow* in S2 is preferred in the context of the current network of sentences.The table below presents the x_j values after calculation of the $\Delta\ x_j$ in equation at (1).

Node	t	$t+1$	t_{Stab}
bow_{S_1} - $ribbon_{S_1}$	9.212	8.862	8.082
bow_{S_2} - $arrow_{S_2}$	9.218	8.470	**8.679**

The table below shows the results for the two homonymous *bow* nodes in the same experiment after the calculation of the $\Delta\ z_{ij}$ in equation at (2). In both occasions, *Bow* of S2 shows clear salience over *bow* of S1, which suggests that the network has successfully disambiguated the homonym *bow* term. However, notice that the results in the table below after calculation of LTM show better discrimination between the two terms.

Node	t	$t+1$	t_{Stab}
bow_{S_1}	10.051	9.005	8.677
bow_{S_2}	8.715	9.184	**9.912**

Further work should investigate the pattern of rebounds and oscillations of x_j until stabilization, as well as the role of the parameters in the overall pattern of the $\Delta\ z_{ij}$.

4. Conclusions

The CLAR-NET network models natural language semantics and meaning as resonance. It is capable of learning to satisfactory resolve ambiguity and perform conceptual discrimination. It plausibly and with biological faithfulness represents both STM activation and LTM learning in a unified fashion (i.e. within the same model), and achieves better results due to LTM modeling. In sum, this is a promising, biologically-faithful blueprint for natural language processing and conceptual representation.

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