A Hybrid Symbolic-Connectionist Processor of Natural Language Semantic Relations

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***Abstract*—In the field of Natural Language Processing (NLP), there are symbolic and connectionist approaches to account for semantic issues, such as the thematic role relationships between sentence constituents. A "hybrid" option merges both methods: a symbolic thematic theory is used to supply the connectionist network with initial knowledge. This way, benefits of connectionism, such as learning, generalization and fault tolerance are combined with representational symbolic features. A symbolic-connectionist hybrid system called HYBθPRED (HYB*rid symbolic-connectionist thematic (θ)* PRED*ictor*) is proposed here. Its main purpose is to reveal the thematic grid assigned to a sentence. The connectionist architecture comprises, as input, a featural representation of the words (based on the verb/noun WordNet classification and on the classical semantic microfeature representation), and, as output, the thematic grid assigned to that sentence. HYBθPRED "predicts" thematic (semantic) roles assigned to words in a sentence context, adopting a psycholinguistic view of thematic theory.**

I. INTRODUCTION

THE GOVERNMENT AND BINDING linguistic theory [2] refers to the semantic roles words usually have in relation to a verb as *thematic roles* (θ-roles). In sentences such as (1), there is an AGENT (*the chef*) and a PATIENT (*the frozen meat*), so that it is said that the verb *thaw* assigns a thematic grid with the roles [AGENT, PATIENT] to this sentence. But, for other sentences with the same verb, this structure can change. So, to sentence (2), *thaw* assigns a different thematic grid, since *wind* is CAUSE, instead of AGENT. The difference between (1) and (2) is due to semantic properties of the subject of verb *thaw* - the animate noun *chef* in (1) in relation to the inanimate *wind* in (2).

The chef thawed the frozen meat, (1)

The wind thawed the ice cream. (2)

Thematic theory in linguistics is symbolic. As in predicate logic, the linguistic expressions are decomposed into a central predicate (often the verb) and a number of arguments that complete its meaning. The predicate assigns thematic roles to the arguments so each sentence can be associated with a thematic grid.

Two decades ago, McClelland and Kawamoto [16] proposed a system to deal with relationship patterns. Their system handled those patterns - the words of a sentence - in order to assign the correct case role to its constituents. Here, another Natural Language Processing (NLP) system, called HYBθPRED (which stands for HYB*rid symbolic-connectionist thematic (θ)* PRED*ictor*), is proposed to identify the thematic grid assigned to a semantically sound input sentence. This system, based on linguistic thematic theory, incorporates many features including dealing with lexical and *thematic* ambiguities. HYBθPRED departs from a symbolic knowledge base concerning thematic roles, and after training, shows the thematic grid assigned to a sentence, one role at a time. In addition, a revised symbolic theory can be extracted from the connectionist architecture.

HYBθPRED receives the sentence as input, presented in verb-noun pairs. Only meaningfully well-formed sentences belong to its training set. The motivation for this comes from the necessity of clarifying some psycholinguistic issues, concerning essentially language acquisition. In order to achieve a complete and sound thematic processing, the words in a sentence must be related to each other, and not only to the verb.

The next section presents thematic roles under a psycholinguistic view. Section III describes the connectionist representation of the adopted input data, which are distributed and based on a semantic feature set. In section IV, there is an introduction to symbolic-connectionist hybrid systems, their advantages and drawbacks. And finally, in section V, the proposed system HYBθPRED is presented, with concluding remarks in section VI.

II. THEMATIC ROLES

The Government and Binding linguistic theory [2], [3] states that thematic roles - the semantic relations between words in a sentence - are in the lexicon, so a specific verb assigns a single thematic grid, the structure containing the thematic roles assigned to a sentence. This is a "slot and filler" lexicalist view. For instance, the verb *judge* would assign an EXPERIENCER (*i*) and a THEME (*j*), no matter in which sentence it occurs, like in $[I]_i$ *cannot judge* [*some works of modern art*]$_j$ [25]. There are verbs, however, which assign different thematic grids to different sentences (*thematically ambiguous* verbs), for instance the verb *thaw* in sentences (1) and (2).

To the sentences (1) and (2), although the same verb is employed, are assigned different thematic grids. In one possible reading of sentence (1), the thematic grid assigned is [AGENT, PATIENT] and in sentence (2), [CAUSE, PATIENT]. The reason is that *the chef*, in the intended reading of sentence (1), is supposed to have the *control of action*, that

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is, the intention of thawing. The same does not occur in sentence (2). *The wind* is not willing of thawing anything.

Thus, a small set of features can be associated with the verb, in the same manner that nouns are associated with a set of (different) features. The componential features associated with the verb change according to the sentence in which the verb is used. So, it is inadequate to say that a specific verb assigns a single thematic grid, because this will depend on the whole sentence in which the verb occurs. In sum, a non-lexicalist approach is preferable [26].

In HYBθPRED, the output units constitute the thematic grid assigned to a sentence, which is composed of up to seven thematic roles: AGENT, EXPERIENCER, CAUSE, PATIENT, THEME, LOCATION, and VALUE. For HYBθPRED, some intuitive thematic role definitions are adopted, as follows. AGENT is the argument that controls the action expressed by the predicate. EXPERIENCER is a participant who does not have the control of an action and usually expresses a psychological state. CAUSE is the argument that initiates the action expressed by the predicate without controlling it. PATIENT is the participant affected directly by the action of the predicate, usually changing states. THEME is the participant affected indirectly by the action of the predicate, without changing states. LOCATION represents the place where the event expressed by the verb occurs or is direct to. VALUE is the argument that stresses the importance of something or somebody.

A set of fifteen verbs from WordNet was chosen for HYBθPRED: *dress*, *warm*, *judge*, *talk*, *fight*, *eat*, *hit*, *paint*, *feel*, *walk*, *see*, *buy*, *host*, *have*, and *thaw*. From these, four are thematically ambiguous: *hit*, *walk*, *have*, and *thaw*. These verbs represent all kinds of semantic relationships HYBθPRED intends to treat.

In a non-lexicalist view (componential), one could have a representation for thematically ambiguous verbs, like *thaw* in sentences (1) and (2), that would allow them to function as predicates in several sentence types. From the verbs proposed for HYBθPRED, many are thematically ambiguous verbs, so they can assign more than one thematic grid.

III. DISTRIBUTED REPRESENTATIONS IN HYBθPRED

In HYBθPRED, a distributed semantic microfeatural representation is employed, inspired by McClelland and Kawamoto's [16] representation. The chosen features are related to a psycholinguistic thematic theory. For verbs, it is based on *WordNet*[1] classification for verbs [7] and on a thematic framework. For nouns, it is based mainly on WordNet classification for nouns [20]. The chosen semantic features for verbs in HYBθPRED are strongly based on a non-lexicalist representation; that is, the thematic role assignment componentially depends on the whole sentence.

It is important to notice here that the verb microfeatures are chosen in order to encompass the semantic issues considered relevant in a thematic framework. The microfeatures outside this semantic context are not meaningful. They only make sense in a system like HYBθPRED, where the specification of semantic relationships between the words in a sentence plays a leading role.

TABLE I
THE TWENTY FIVE SEMANTIC MICROFEATURE DIMENSIONS FOR VERBS, BASED ON WORDNET VERB CLASSIFICATION AND ON A THEMATIC FRAMEWORK.

10	*01*
body	*no body*
change	*no change*
cognition	*no cognition*
communication	*no communication*
competition	*no competition*
consumption	*no consumption*
contact	*no contact*
creation	*no creation*
emotion	*no emotion*
motion	*no motion*
perception	*no perception*
possession	*no possession*
social	*no social*
stative	*no stative*
weather	*no weather*
control of action	*no control of action*
direct process triggering	*indirect process triggering*
direction of action to source	*direction of action to goal*
impacting process	*no impacting process*
change of state	*no change of state*
psychological state	*no psychological state*
objective action	*no objective action*
effective action	*no effective action*
high intensity of action	*low intensity of action*
interest on process	*no interest on process*

The schema on table I displays the semantic features for verbs. These features are based on WordNet classification for verbs [7] and on a thematic framework. For each of these dimensions, one feature is active, and the other is inactive.

When the user enters a thematically ambiguous verb, like *thaw*, into HYBθPRED, the system does not know which *thaw* is intended. And, the input pattern makes use of a third value to represent uncertainty, in dimensions where the different readings of the word disagree. It means that in cases in which the two readings agree with the values of an input dimension, this dimension holds the agreed value in the input representation. In cases in which the two readings disagree, the feature displays the value 0.5 in the input representation (represented by the "?" sign). The goal is to verify whether the system can come up with the correct values for such unspecified slots or positions in the input array. Therefore, some of the microfeatures will be undetermined and the system should arrive at the missing values for the intended reading of *thaw*.

In addition to the thematic ambiguity of verbs, the system can also handle the problem of lexical ambiguity of nouns. For ambiguous nouns (*bat*, for instance), the input employs a representation similar to that of verbs (values in a three-valued logic).

Table II shows the microfeatures for nouns, based on WordNet classification for nouns [20]. Here, there are two-bit groups representing the semantic features, except for *change*, *cognition*, *communication*, *competition*, *emotion*,

[1] WordNet version 3.0: http://wordnet.princeton.edu/obtain

TABLE II
THE THIRTY SEMANTIC MICROFEATURE DIMENSION GROUPS FOR NOUNS, BASED MAINLY ON WORDNET NOUN CLASSIFICATION.

feature	value 1 (*01*)	value 2 (*10/1*)	value 3 (*11*)
action	act	process	state
life	animal	person	plant
element	artifact	quantity	substance
property	attribute	location	possession
corporeal	body	cognition	feeling
society	commun.	event	relation
nature	time	nat. obj.	nat. phen.
miscellaneous	group	motive	shape
size	small	medium	large
consistency	soft	medium	hard
form	rounded	angular	irregular
fragility	breakable	unbreakable	-
instrument	tool	utensil	food
adulthood	prof. adult	adult	child
gender	male	female	-
body	object	subject	-
change	-	subject	-
cognition	-	subject	-
communication	-	subject	-
competition	-	subject	-
consumption	object	subject	-
contact	object	subject	-
creation	object	subject	-
emotion	-	subject	-
motion	-	subject	-
perception	-	subject	-
possession	object	subject	-
social	-	subject	-
stative	-	subject	-
weather	-	subject	-

Legend: commun. = communication, nat. obj. = natural object, nat. phen. = natural phenomenon, prof. adult = professional adult. A fourth value should be included in each line representing "not applicable": (*00/0*).

motion, *perception*, *social*, *stative*, and *weather*, which are represented by only one bit.

IV. SYMBOLIC-CONNECTIONIST HYBRID SYSTEMS

Since its inception, Artificial Intelligence (AI) is torn between two opposing fields: the symbolic paradigm, based on logic, and the connectionist paradigm, based on the propagation of the activity of elementary processors.

Artificial neural networks are not adequate for manipulation of high level symbols [8]. They are usually preferred in a number of situations (such as pattern recognition) because they are able to generalize over the inputs, they are fault tolerant, and exhibit the ability to learn from experience.

But, their critics emphasize that they lack transparency, that is, one does not know how they work, how they develop internal representations. This is a huge drawback. For instance, it is not easy to ascertain the meaning of the connections and their weights or the configuration of the hidden layers as regards a certain input-output pair. In addition, it is known that the training step often takes too long.

An answer to such criticism is the so-called Knowledge-Based Neural Networks, or Symbolic-Connectionist Hybrid Systems, which bring the opposing AI paradigms into closer contact, allowing for symbolic knowledge to be introduced in as well as extracted from neural networks [5]. In these systems one can combine symbolic approach benefits, like expressive power of general logical implications, ease of knowledge representation, and understanding through logical inference, with connectionism advantages already mentioned.

The extraction of symbolic knowledge from trained artificial neural networks permits the exchange of information between connectionist and symbolic knowledge representations and has been of great interest to understand what the artificial neural network actually does [30]. Additionally, a significant decrease in training time can be obtained by training networks with initial knowledge [22].

In a symbolic-connectionist hybrid approach, symbolic rules are inserted in a connectionist architecture as connection weights. The network is submitted to a training period, like conventional connectionist systems. After training, the symbolic theory, which gave initial knowledge to the network, had been revised by the connectionist learning. The symbolic knowledge generated by the net can be extracted in a way comparable to initial symbolic knowledge insertion.

Since symbolic-connectionist hybrid systems include initial knowledge, training is supposed to take less time. In the hybrid approach adopted here, the symbolic knowledge is represented through connection weights between artificial neural network processing units. For instance, a connectionist schema, as shown in figure 1, can represent a logical rule (Eq. (3)), with weighed antecedents A and B, and consequent C. The antecedents are weighed, because w_{AC} and w_{BC} (connection weights) are not binary values but real numbers. Also, it simulates an *and* unit, such that only the presence of both inputs A and B causes unit C to be activated.

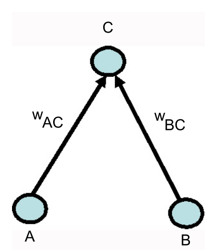

Fig. 1. A schema for the rule $(w_{AC} * A)$ and $(w_{BC} * B) \rightarrow C$.

$$(w_{AC} * A) \text{ and } (w_{BC} * B) \rightarrow C. \qquad (3)$$

Although many researchers believe that symbolic and connectionist systems are so different that they are irreconcilable, others emphasize that the integration of both is not only possible but also crucial for the systems "understand" cognition behind computational implementations [13].

V. THE HYBθPRED SYSTEM

In this section, the HYBθPRED system is presented: its connectionist architecture, the supervised learning algorithm, and simulation experiments: the way training sentences are generated, the inclusion of initial symbolic data, training, and the extraction of symbolic data, which confirm the expected data and extend initial knowledge. "Hidden" symbolic knowledge, discovered by the network architecture and training is revealed: which category influenced most each thematic role? Is it the noun, to which the role is assigned, or is it the verb, which assigns such role? Results are presented and discussed.

A. HYBθPRED *connectionist architecture*

Unlike McClelland and Kawamoto system [16], in HYBθPRED a single network accounts for each verb-noun pair; thus generalizing over both nouns and verbs. In fact, this is crucial in dealing with thematic roles, for they are but the generalization of semantic relationships between verbs and nouns.

The connectionist network used in HYBθPRED is structured in three layers: the *input layer* with a hundred units, to which the input sentence is made available, word by word; the *hidden layer* with fourteen units, which allows the network to develop internal representations; and the *output layer* with seven units, from which the assigned thematic grid representations are generated by the system.

The implemented architecture is bi-directional, with a hundred input units, forteen hidden units, and seven output units, one for each of the seven thematic roles: AGENT (A), PATIENT (P), EXPERIENCER (E), THEME (T), LOCATION (L), CAUSE (C), and VALUE (V). In this case, the architecture classification schema, according to Sun [32], can be *single-module*, employing distributed representation. Each sentence is presented one word at a time to the hundred-unit input layer α (see figure 2). Notice that there are different slots for verbs and nouns. Notice also the bi-directional links between hidden (β) and output (γ) layers, while there are unidirectional links from input (α) to hidden (β) layer.

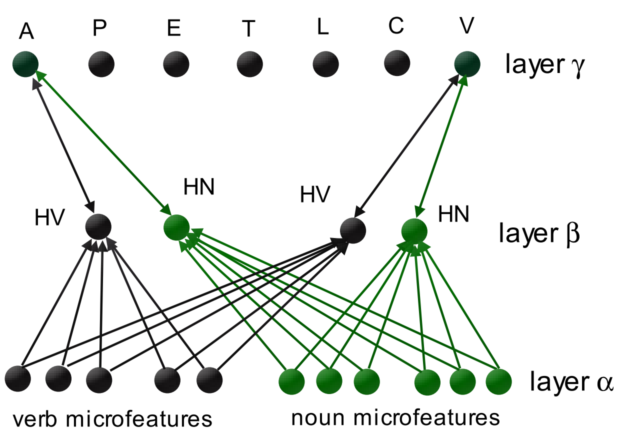

Fig. 2. HYBθPRED bi-directional architecture.

B. Biologically plausible supervised learning

For each sentence presented, an output is computed, based on the input pattern and on the current values of net weights. The actual output can be quite different from the "expected" output, i.e. the values that it should have in the correct reading of the sentence, that is, the correct thematic grid assigned to the input sentence. During training, each output is compared to the correct reading, supplied as a "master input." This master input should represent what a real language learner would construct from the context in which the sentence occurs. Learning may be described as the process of changing the connection weights to make the system output correspond, as close as possible, to the master input.

Instead of the computationally successful, but considered to be biologically implausible [4] supervised Backpropagation [27], the learning algorithm BIO*Rec* employed in HYBθPRED is inspired by the Recirculation [12] and GeneRec [23] algorithms. Other applications of this algorithm can be verified in [24] and in [28].

C. Simulation experiments

In this subsection, simulation experiments for HYBθPRED are presented. Training sentences represented by their semantic microfeatures are entered, word by word, to the input layer α (training step). Each sentence is accompanied by its thematic grid since the adopted training algorithm BIO*Rec* is supervised. After training, test sentences are entered in order to check the system learning of the correct thematic grids (recognition step).

During training, the system employs a sentence generator which generates only semantically well-formed sentences. That is, in training, there are no undetermined input values. Every (lexically or thematically) ambiguous word is related to a specific meaning regarding the sentence in which it occurs. After training, when the user enters a thematically ambiguous verb (or a lexically ambiguous noun), the word is simply entered as it is written, that is, without any additional semantic information. So, since at input layer the word comes apart from the sentence, it is unknown which meaning is intended. In this case, some semantic microfeatures have their values "undetermined." The system will arrive to the correct value because it learned sentence patterns with the two readings, so, based on context, it is able to "discover" which is the correct reading (a kind of pattern recognition).

1) The cycle of symbolic data in the symbolic-connectionist hybrid HYBθPRED*:* The cycle of symbolic data insertion and extraction into/from HYBθPRED is shown in figure 3, adapted from Taha and Ghosh [33]. Instead of beginning with random connection weights (no initial knowledge), HYBθPRED starts with some biased symbolic knowledge inserted into the connectionist architecture, and, through a learning procedure that makes use of a sentence generator, produces final symbolic data. The sentence generator employs a training set, consisting of syntactic and semantically sound sentences provided by a symbolic theory. Symbolic data, extracted from the connectionist architecture after learning, revise the initial symbolic theory and provide up-to-date information for the sentence generator. It had been proved that the set of rules and the network, from which it is extracted, are equivalent [13].

2) Initial symbolic knowledge insertion and training: After the introduction of initial symbolic knowledge concerning

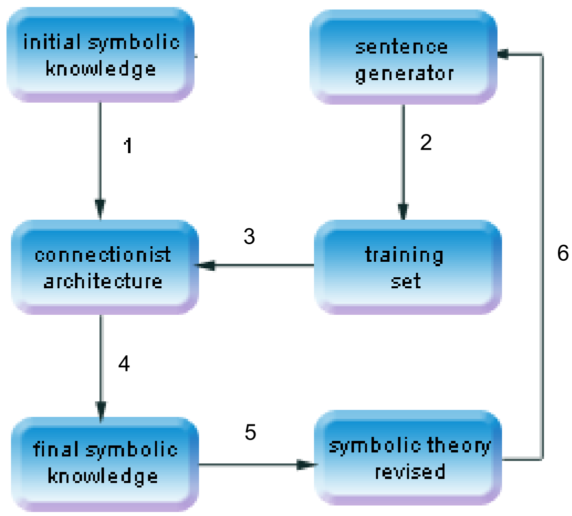

Fig. 3. The cycle of symbolic data insertion and extraction into/from a connectionist architecture. Steps: (1) Initial symbolic knowledge is inserted as synaptic weights into the network; (2) The sentence generator supplies semantically sound sentences for training; (3) Training sentences feed the connectionist architecture; (4) After learning is finished, final symbolic knowledge is extracted from the connectionist architecture; (5) Final knowledge is used to revise the initial symbolic theory; (6) The revised symbolic theory provides up-to-date information for the sentence generator.

thematic roles as connection weights, the network begins to learn through presentations of semantically sound sentence-thematic grid pairs. The sentence generator produces the input sentences.

Initial knowledge is inserted based on the architecture displayed in figure 2. In this architecture, symbolic concepts about verbs and nouns are mapped on to network elements, according to the hybrid approach as shown in figure 1. As mentioned before, the symbolic knowledge is represented through connection weights between network units. So, logical rules with weighed antecedents can be obtained.

Negative and positive values for nouns and verbs are assigned. In the hidden layer β there are the conjunction of the verb inputs in *HV* and the conjunction of the noun inputs in *HN*. These two units are connected to one unit in the output layer γ, corresponding to a specific thematic role.

Symbolic knowledge regarding a thematic framework is considered in the symbolic-connectionist hybrid system HYBθPRED. Initial "symbolic thematic rules" for verbs are implemented for each one of the thematic roles [10], [18]. For nouns, there are initial rules only for the thematic roles AGENT and CAUSE, because both may be assigned to subjects of thematically ambiguous verbs. The other thematic roles are considered noun-independent.

For each thematic role there are two "hidden" rules whose antecedents map the units belonging to the input layer and whose consequents map hidden units - one for the verb (*HV*), and the other for the noun (*HN*) (see figure 2).

3) Final symbolic knowledge extraction: After about 45,000 training cycles, which corresponds to an average output error[2] of 10^{-3}, the system will be able to predict the thematic roles assigned to an input sentence.

In relation to accuracy, the system presents precision rate of 94%[3], since only seven words revealed inadequate thematic roles in 120 words belonging to test sentences, in a limited, but sufficient, set of test sentences.

As soon as training finishes, the symbolic rules can be obtained from the architecture by running an extraction procedure [9], [29], [34]. Rule extraction consists in reversing the process of initial rule insertion. That is, the net weights are assessed and a weighed antecedent is obtained, corresponding to the connection weight. The symbolic knowledge thus extracted from the present connectionist architecture corresponds to the network learning and generalization capacities. As a consequence, the network is able to "revise" the initial symbolic rules.

Initial and extracted rules for the seven thematic roles are presented below. Initial rules for nouns are included only for AGENT and CAUSE, in order to facilitate the distinction between them. Extracted rules for nouns are only displayed for thematic roles which depend on semantic features of nouns, that is, for PATIENT, EXPERIENCER, LOCATION, CAUSE, and VALUE. The semantic microfeatures are in *italics* and are weighed by a normalized real number. Only microfeatures representing relevant semantic features for the thematic role (weight above 50%) are displayed. The closer to 1.0, the more precise is the value. In order to understand the conjunction of extracted rules see figure 2:

AGENT

initial hidden rule for verb:

If verb comprises (*control of action*) and (*direct process triggering*) and (*impacting process*) and (*objective action*) and (*interest on process*) then HV_{AGENT}

initial hidden rule for noun:

If noun is (*person*) and (*body-subject*) and (*no cognition*) and (*competition*) and (*creation-subject*) then HN_{AGENT}

extracted hidden rule for verb:

If verb comprises (0.9 *no change*) and (0.8 *no contact*) and (0.5 *no weather*) and (0.9 *control of action*) and (0.8 *direction of action to source*) and (0.9 *objective action*) and (1.0 *interest on process*) then HV_{AGENT}

extracted final rule:

If 1.0 HV_{AGENT} and -0.1 HN_{AGENT} then thematic role = AGENT

[2]The average output error is the difference between "actual" output and "expected" output, and it is obtained from the average squared error energy formula [11] for each set of different sentences presented to the network.

[3]Here, *precision* is the number of correct answers given by the system divided by the number of answers given by the system [15].

PATIENT

initial hidden rule for verb:

If verb comprises (*direction to goal*) and (*impacting process*) and (*change of states*) and (*effective action*) and (*high intensity of action*) then HV_{PATIENT}

extracted hidden rule for verb:

If verb comprises (0.9 *body*) and (0.7 *change*) and (0.9 *cognition*) and (1.0 *communication*) and (0.6 *competition*) and (1.0 *consumption*) and (0.9 *creation*) and (0.7 *emotion*) and (0.7 *perception*) and (0.7 *possession*) and (0.9 *social*) and (0.9 *stative*) and (0.9 *weather*) and (0.7 *impacting process*) and (0.7 *psychological state*) and (1.0 *high intensity of action*) then HV_{PATIENT}

extracted hidden rule for noun:

If noun is (1.0 *process*) and (0.8 *large*) and (0.7 *hard*) and (1.0 *creation-object*) and (0.5 *motion*) and (0.9 *social*) and (0.7 *stative*) then HN_{PATIENT}

extracted final rule:

If 0.5 HV_{PATIENT} and 1.0 HN_{PATIENT} then thematic role = PATIENT

EXPERIENCER

initial hidden rule for verb:

If verb comprises (*direction to source*) and (*no change of states*) and (*no objective action*) and (*no interest on process*) then $HV_{\text{EXPERIENCER}}$

extracted hidden rule for verb:

If verb comprises (1.0 *cognition*) and (0.5 *no social*) and (0.8 *stative*) and (0.5 *no control of action*) and (0.7 *indirect process triggering*) and (0.6 *direction of action to source*) and (0.9 *psychological state*) and (0.6 *no objective action*) and (0.5 *no effective action*) then $HV_{\text{EXPERIENCER}}$

extracted hidden rule for noun:

If noun is (1.0 *consumption-subject*) and (1.0 *contact-subject*) and (0.6 *perception*) and (0.6 *possesion-object*) then $HN_{\text{EXPERIENCER}}$

extracted final rule:

If 0.9 $HV_{\text{EXPERIENCER}}$ and 1.0 $HN_{\text{EXPERIENCER}}$ then thematic role = EXPERIENCER

THEME

initial hidden rule for verb:

If verb comprises (*direction to goal*) and (*no impacting process*) and (*no change of states*) and (*effective action*) and (*low intensity of action*) then HV_{THEME}

extracted hidden rule for verb:

If verb comprises (1.0 *body*) and (0.7 *change*) and (0.9 *cognition*) and (1.0 *communication*) and (0.9 *competition*) and (1.0 *consumption*) and (1.0 *creation*) and (1.0 *emotion*) and (0.6 *motion*) and (0.7 *perception*) and (0.7 *possession*) and (0.9 *social*) and (0.9 *stative*) and (1.0 *weather*) and (0.9 *psychological state*) then HV_{THEME}

extracted final rule:

If 1.0 HV_{THEME} and 0.4 HN_{THEME} then thematic role = THEME

LOCATION

initial hidden rule for verb:

If verb comprises (*control of action*) and (*direct process triggering*) and (*direction to goal*) and (*no change of states*) and (*effective action*) then HV_{LOCATION}

extracted hidden rule for verb:

If verb comprises (0.9 *no cognition*) and (0.7 *social*) and (1.0 *control of action*) and (0.6 *direct process triggering*) and (0.8 *no psychological state*) and (0.9 *objective action*) and (0.6 *interest on process*) then HV_{LOCATION}

extracted hidden rule for noun:

If noun is (0.6 *location/possession*) and (0.7 *attribute/possession*) and (1.0 *motion*) then HN_{LOCATION}

extracted final rule:

If -0.1 HV_{LOCATION} and 1.0 HN_{LOCATION} then thematic role = LOCATION

CAUSE

initial hidden rule for verb:

If verb comprises (*no control of action*) and (*indirect process triggering*) and (*no objective action*) and (*no interest on process*) then HV_{CAUSE}

initial hidden rule for noun:

If noun is (*animal*) and (*artifact*) and (*natural phenomenon*) and (*no body-subject*) and (*no competition*) and (*contact-subject*) and (*no creation-subject*) and (*weather*) then HN_{CAUSE}

extracted hidden rule for verb

If verb comprises (1.0 *change*) and (0.9 *contact*) and (0.7 *weather*) and (1.0 *no control of action*) and (0.9 *direction of action to goal*) and (1.0 *no objective action*) and (1.0 *no interest on process*) then HV_{CAUSE}

extracted final rule:

If 1.0 HV_{CAUSE} and 0.5 HN_{CAUSE} then thematic role = CAUSE

VALUE

initial hidden rule for verb:

If verb comprises (*control of action*) and (*direct process triggering*) and (*no change of states*) and (*effective action*) and (*interest on process*) then HV_{VALUE}

extracted hidden rule for verb

If verb comprises (0.9 *no cognition*) and (0.7 *social*) and (1.0 *control of action*) and (0.7 *direct process triggering*) and (0.9 *no psychological state*) and (0.9 *objective action*) and (0.7 *interest on process*) then HV_{VALUE}

extracted hidden rule for noun:
If noun is (1.0 *motion*) then HN_{VALUE}

extracted final rule:
If -0.1 HV_{VALUE} and 1.0 HN_{VALUE} then thematic role = VALUE

The schema above shows initial and extracted rules for thematic roles. For instance, taking the rules for AGENT, one can notice that all the microfeatures considered relevant as initial knowledge were highlighted by connectionist learning, mainly *control of action*, *objective action*, and *interest on process*. The system discovered new semantic features for the verb that assigns the thematic role AGENT: *no change*, *no contact*, *no perception*, *weather*, *direction of action to source*, and *no effective action*.

The noun to which is assigned the thematic role AGENT is not taken into consideration, since the “output” rule shows no significant value for HN_{AGENT}.

Notice that, when initial knowledge is input to the system (for verbs), there is a tendency of strengthening the initial weights. This can only be taken as evidence that the final weights reflect the available symbolic knowledge (about a thematic role) from the examples and from the architecture, in cases when initial weights are arbitrary.

D. Some features are discovered to be complementary

HYBθPRED is able to classify and categorize the intended mutually exclusive microfeatures within a sub-array, and subsequently to adjust the weights connecting hidden units to output units in order to correctly reveal the thematic assignment for each pair verb-noun in a sentence. This is attributed to the fact that the network architecture, in addition to initial biasing, induces the connection weights related to pairs of semantic features to be taken as complementary. That is, some sort of internal representation of implications has been developed for thematic roles, which are not introduced as inputs to the network (see figure 4). This kind of network “discovery” is believed to be extremely important, because even without initial knowledge, the network is able to classify and categorize the intended mutually exclusive microfeatures within a subset [26].

E. Which lexical category is the most important to each thematic role?

Relevant information regarding the importance of lexical categories to a specific thematic role can be obtained through extracted symbolic rules. Consider table III. Some are worthy of mention: AGENT, THEME, and CAUSE are the thematic roles which depend crucially on verbs, especially AGENT, for which the difference between verb and noun normalized weights is greater than 1; and PATIENT, LOCATION, and VALUE are the thematic roles which depend crucially on nouns, especially LOCATION and VALUE. Another interesting thematic role is EXPERIENCER: it depends almost equally on verb and noun (difference of 0.1).

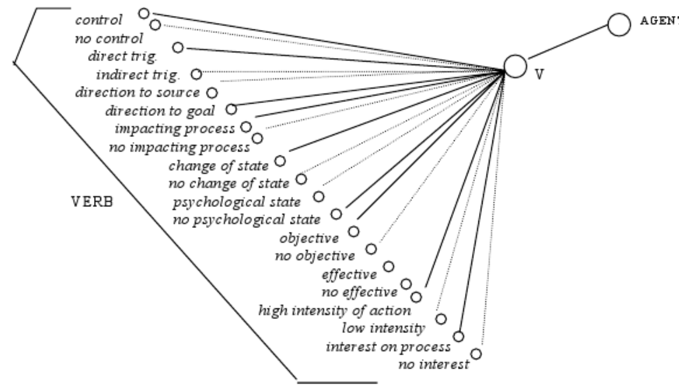

Fig. 4. Part of semantic microfeature array of the verb regarding the thematic role AGENT, showing complementarity between features inside dimensions. Full lines represent positive weights and dotted lines represent negative weights. Notice that, except for *effective action*, all the other items are complementary. In this case, the network learning considered irrelevant the feature *effective action* for thematic role AGENT.

This means that, in order to assign the thematic role AGENT, the verb practically does not take into account the features of the noun, to which the role is assigned. Most of the cases, only the verb influences directly the choice of this thematic role. Alternatively, for an assignment of the thematic role VALUE, the noun itself is enough to “receive” the role, regardless of the verb which is assigning it. However, for the thematic role EXPERIENCER, both noun and verb are important for the assignment.

The fact that, in most cases, the verb, regardless of the features of the noun, assigns the thematic role AGENT to that noun is a big problem to the so-called thematically ambiguous verbs. Take again, for instance, sentences (1) and (2). How HYBθPRED could associate the thematic role CAUSE to the subject of sentence (2), if the verb *thaw* assigned the thematic role AGENT to the subject of sentence (1)?

Of course, the system could be “confused,” but during training it receives a lot of sentences employing thematically ambiguous verbs, like *thaw*, including sentences in which the subject is CAUSE, not AGENT. This way, HYBθPRED can learn the correct assignment and be able to distinguish between one role and another. Certainly, this is possible if and only if, in addition to the verb, the features of the noun are also taken into account.

VI. CONCLUSION

In the field of connectionist NLP, several systems [1], [14], [16], [17], [19], [31] use the notion of thematic role modeling. The system HYBθPRED departs from all these in that it relies on the role of semantic entailments in thematic relations, i.e., in the way it makes use of theoretical knowledge from linguistics.

HYBθPRED implements a symbolic-connectionist hybrid approach to thematic role processing. In this approach, the

TABLE III

HYBθPRED "OUTPUT" RULES. FOR EACH THEMATIC ROLE, IT IS POSSIBLE TO INFER WHICH LEXICAL CATEGORY IS MORE RELEVANT, THROUGH NORMALIZED EXTRACTED WEIGHTS.

theta-ROLE	*verb weight*	*noun weight*
AGENT	**1**	-0.1
PATIENT	0.5	**1**
EXPERIENCER	**0.9**	**1**
THEME	**1**	0.4
LOCATION	-0.1	**1**
CAUSE	**1**	0.5
VALUE	-0.1	**1**

advantages of symbolic systems (ease of knowledge representation, understanding through logical inference, etc.) are combined with the advantages of connectionism (learning, generalization, fault tolerance, etc.) to yield a more discriminating thematic role processing, that is sensitive to the subtleties involved in such linguistic phenomenon.

In connectionist NLP systems, the words belonging to a sentence must be represented in such a way as to keep the meaning of the words and, at the same time, to be useful for the network to develop significant internal representations. The representation of semantic features adopted in this system would also easily allow for new words to be entered in order to increase its lexicon, provided that their semantic microfeature arrays are supplied.

HYBθPRED adopts pre-specified semantic microfeatures, although its microfeatures are based on WordNet, which is considered an ontology based on semantics [21]. In addition, there is a psycholinguistic concern about which features should be considered important in a thematic framework.

In this system, the architecture employed is feed-forward, although bi-directional. A recurrent architecture, in the sense of Elman [6] was also considered, but it proved to be not as efficient as the bi-directional feed-forward version, although it is well known that recurrent architectures are adequate to temporal processing tasks, like NLP.

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