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HIERARCHICAL STRUCTURES

CONNECTIONISM VS. DETERMINISM

Katerina Čundeva

Abstract. Hierarchical markers used for coding headwords in dictionary determined neural network architecture for Machine translation. Their creation was completely algorithmic. This paper presents the attempts for replacing deterministic approach with connectionist.

Key words: Machine Translation, Neural Networks, Set Theory

1. Introduction

Machine Translation System between Macedonian and English language [3,4] pases through four phases:

- curriculum
- monolingual training
- testing known and novel sentences
- learning with partial and complete re-training

Although major part of the MT system is connectionist, preparation for the curriculum is still deterministic. It deals with the creation of monolingual hierarchical networks which are essential for neural network architecture. Could this algorithmic approach be avoided and replaced with pure connectionist?

This paper presents the first attempts towards this goal. It is based on and tested with the original network creation concept. The theorem which guarantees the usefulness of the algorithm for machine translation [2,5] is also presented and tested.

2. The most elementary hierarchical networks

It is not an exaggeration to claim that verbs have the major importance in sentence understanding and translation [6,7,8,9]. And if they are some kind of governors, it is natural to use them as central point not only in syntactic but also in semantic and contextual analysis.

Hierarchical networks were inspired by semantic nets [1,2,7] and they are in some extent their modification. They are used for coding the headwords in monolingual and bilingual dictionary. In the connectionist based MT system the names of hierarchical classes joined with the grammatical category of the words determine the set of processing units.

The main goal of hierarchical networks is noun distribution in mutually dependent sets and subsets [2]. The division of the nouns depends on the verbs they are related to. As first, they are syntactically divided into subject and object classes sorting out from main noun class. Part of the subjects are capable of doing the action carried by the verb, but some of them are not, so all subjects related to same verb are connected in a common class which is a disjunctive union of two subclasses with opposite logical value.

Hierarchical networks are presented by the triple M=(X,H,L) where **X** is the set of all nodes, **H** a set of (parent, child) related couples, and **L** a set of logical binary relations between subject and object nodes. Each sentence isolated from the text defines its own smaller network. The first part of creation algorithm is composition of such smaller networks into a common one. In the most elementary case, M1=(X1,H1,L1) and M2=(X2,H2,L2) are two networks obtained from two sentences with several subjects and objects. They determine these relations:

Hierarchical:

$$NX1=A1^{(1)} \cup A2^{(1)} \quad A1^{(1)}=\{a,b,c,d\}$$
$$A2^{(1)}=B1^{(1)}+B2^{(1)} \quad B1^{(1)}=\{E,F,G,H,I\} \quad B2^{(1)}=\{J,K,L,M,N\} \qquad (1)$$

$$NX2=A1^{(2)} \cup A2^{(2)} \quad A1^{(2)}=\{x,y,z\}$$
$$A2^{(2)}=B1^{(2)}+B2^{(2)} \quad B1^{(2)}=\{E,F,J,K,O\} \quad B2^{(2)}=\{G,H,L,M,P\} \qquad (2)$$

Logical:

$$B1^{(1)} \text{ V1 affirmative } A1^{(1)} \quad B2^{(1)} \text{ V1 negative } A1^{(1)}$$
$$B1^{(2)} \text{ V2 affirmative } A1^{(2)} \quad B2^{(2)} \text{ V2 negative } A1^{(2)} \qquad (3)$$

The structure of the composition depends on the relation between the verbs found in the sentences. Three different situations can occur:

1. V1 = V2 translation(V1) = translation(V2)
2. V1 = V2 translation(V1) $\neq$ translation(V2)
3. V1 $\neq$ V2

The equality of the action carried by the verb in both languages (case 1.) implies that intersection between object sets from both networks exists. For example, a $\equiv$ x and b $\equiv$ y. This is also possible when the sentences contain different verbs (case 3). In these two cases common network consists of three subclasses: both differences and the intersection. In the second case object classes remain the same. Subject classes determine four intersections and four differences made of subclasses and common class (for example: $B1^{(1)}\backslash A2^{(2)}$). Logical relations of novel components are inherited from the classes they were made of. They will be discussed in details in the chapter 4. of this paper.

The process of network creation is iterative and it continues after each new sentence. The usefulness of the algorithm is guaranteed with following theorem.

Definition: Let M1 = (X1,H1,L1) and M2 = (X2,H2,L2) be two hierarchical networks. If a bijective correspondence:
f: X1 > X2 exists such that:

(i) $H1 = \{(y1,y2) \mid y1 \in X1, y2 \in X1, y1\ \rho\ y2\}$, if and only if
$L2 = \{(f(y1),f(y2)) \mid y1 \in X1, y2 \in X1, f(y1)\rho f(y2)\}$

(ii) $H1 = \{(z1,z2) \mid z1 \in X1, z2 \in X1, z1\ \beta\ z2\}$, if and only if
$L2 = \{(f(z1),f(z2)) \mid z1 \in X1, z2 \in X1, f(z1)\rho f(z2)\}$

then M1 $\cong$ M2, i.e. the networks M1 = (X1,H1,L1) and M2 = (X2,H2,L2) are isomorphic. •

<u>Theorem</u>: Two hierarchical networks obtained from the same corpus with different sentence orders are isomorphic.

3. Setting up the scene

Auto-associative model used in previous researches ([2], [3], [4] and others) fulfilled the expectations, so it was applied for this study again. The set of processing units consisted of the classes given in (1) and (2), a couple of mutually exclusive sentence units and a couple of verb units for each different appearance of the verb.

The network was trained with basic and additional patterns. Basic patterns for all three cases represented four sentences given in (3). They were presented twice in pattern file. The set of hierarchical relations given in (1) and (2) was enlarged with relations connecting the opposite form of same verb.

Additional patterns were responsible for potential relation between subject from one and objects from other sentence. These relations were added:

1. 4 affirmative and 4 negative sentences with $A1^{(i)}$, V1 and $B_j^{(2-i)}$, $i,j \in \{1,2\}$
2. 4 affirmative and 4 negative sentences with $A1^{(i)}$, Vi and $B_j^{(2-i)}$, $i,j \in \{1,2\}$
3. 8 affirmative and 8 negative sentences with $A1^{(i)}$, Vk and $B_j^{(2-i)}$, $i,j,k \in \{1,2\}$

A criterion for successful training was total error smaller than 0.1 for basic sentence patterns, 0.5 for hierarchical relations and 1.0 for additional patterns. Training conditions were extremely strict, so each network passed through at least 20000 epochs. After finishing this research the model was re-trained and tested in less precise environment and the results were almost equal.

4. What did the model learn

After training was over the testing started. At the beginning tested were separately all potential intersections and differences between the objects and between the subjects. The intersections were simulated by double affection of corresponding units, while the difference was simulated by affected first and either inhibited or idle second unit. In order to get information about logical relations the patterns were treated in sentence context,so verb and sentence units were excited. Logical relations which could not be found were additionally tested in whole. In several situations excitation of verb units seemed to be obsolete, so the same patterns were also tested, this time with idle verb units. The criteria for judging the correctness of tested pattern were its total error and the internal input to the units.

The results of the most illustrative tests are given in the appendices A,B and C of this paper. Each appendix treats one of the cases defined in chapter 2. Here are the conclusions:

1. Both networks contain the same verb

- •all relations between object sets are almost equally possible (Table 1.)
- •all intersections between subject sets exist (Table 2.)
- •differences between subject subsets exist (Table 3.)
- •relations between the subsets from both networks are symmetrical (Tables 1., 2. & 4.)
- •Final consIucion: The theorem is correct

The new main object class was renamed into A1. It was divided into three subclasses:

$$B1=A1^{(1)}\backslash A1^{(2)} \quad B2=A1^{(1)} \cap A1^{(2)} \quad B3=A1^{(2)}\backslash A1^{(1)} \qquad (4)$$

New subject class called A2 was divided into eight smaller sets:

$$B4=B1^{(1)}\cap B1^{(2)} \quad B5=B1^{(1)}\backslash A2^{(2)} \quad B6=B1^{(1)}\cap B2^{(2)} \quad B5=B1^{(2)}\backslash A2^{(1)}$$
$$B8=B2^{(1)}\cap B1^{(2)} \quad B9=B2^{(1)}\backslash A2^{(2)} \quad B10=B2^{(1)}\cap B2^{(2)} \quad B11=B2^{(2)}\backslash A2^{(1)} \qquad (5)$$

The results given in Table 1. indicated that affirmative connections could be expected when $B1^{(1)}$ and $B1^{(2)}$ were affected at the same time. With same probability and error, negative relations existed whenever second subject classes $B2^{(1)}$ and $B2^{(2)}$ were affected. Logical relations between B4 and B10 with subject classes were completely clear (6, 12). The same results were obtained when subject intersection couples were tested. Whenever subjects with opposite relation to the main verb were excited both object units $A1^{(1)}$ and $A1^{(2)}$ had exactly the same affection. Nothing could be concluded about their mutual relationship.

In all tests performed to check the presence of subject differences with both excitations of the second unit (inhibited or idle) the class it was belonging to was undoubtedly inhibited. Therefore object subsets were replaced with their parental classes (B5, B7, B9 and B11). Similarly to previous cases the excitation of symmetrical patterns was equal.

After the last testing (Table 4.) some of missing logical relations were found. Anyway, for each subject one of them was ambiguous. For example, it was not possible to discover whether or not the subject I∈B5 did the action to the object z∈**B3**. The same kind of ambiguity appeared with B7, B9 and B11.

For B6 and B8 the problem was which relation with the common subject set should be considered correct. Therefore a test with idle verb units was made. Both verb units had equal external input 67 and activation 12, but the error was 4.8786 for B6 (4.8754 for B8) which resolved the problem. In fact such situation is contradictory. It is impossible to find a subject with affirmative and negative action towards same object.

B4 aff. B1	B4 aff. B2	B4 aff. B3	(6)
B5 aff. B1	B5 aff. B2	B5?B3	(7)
B6 aff. B1	B6?B2	B6 neg. B3	(8)
B7?B1	B7 aff. B2	B7 aff. B3	(9)
B8 neg. B1	B8?B2	B8 aff. B3	(10)
B9 neg. B1	B9 neg. B2	B9?B3	(11)
B10 neg. B1	B10 neg. B2	B10 neg. B3	(12)
B11?B1	B11 neg. B2	B11 neg. B3	(13)

2. Same source verb with different target equivalents

- intersection between object sets is probably illegal (Table 5.)
- all intersections between subject sets exist and their logical relations are clearly determined (Table 6.)
- differences between subject subsets exist but they differ for both translations of the verb (Tables 7. & 8.)
- differences between subject subsets and object sets are symmetrical (Table 9.)
- relations between the subsets from both networks are symmetrical
- Final conclusion: The theorem is correct

Potential non-existence of intersections between object sets found during first testing (Table 5.) is also true. Let the action be vozi (drive, ride) in Macedónian. The first translation drive matches with car, van, bus... while bikes, motorcycles, scooters... are ridden. The noun *a* can belong either to one or to another object set never to both of them. This example can be extended to any transitive verb with several meanings.

The intersections between subject sets were tested for both translations of the verb. The results were beyond the expectations because all patterns for both sentence orders were almost identical and all logical relations (6, 8, 10, 12) were found (Table 6.). Both question marks (8,10) were no longer important to the extent that B2 was found excluded from common network.

Subject differences (Tables 7. & 8.) for both translations were again almost identical. Similarly to previous case they were indicating replacement of subject subsets with their parental set (Table 9.). As far as nothing could be concluded about logical relations additional testing was performed (Table 10.), but even then question marks (7, 9, 11 and 13) could not be avoided. Again, it is correct. For example, it is clear that the subject $I \in B1^{(2)} \setminus A2^{(2)}$ does the first action carried by the verb, but whether or not it does the second?

3. Two different verbs

- all relations between object sets are legal (Table 11.)
- all intersections between subject sets exist (Table 12.)
- differences between subject subsets and sets exist (Table 13.)
- relations between the subsets from both networks are symmetrical (Table 14.)
- Final conclusion: The theorem is correct

Similarly to the first case, it was easy to determine logical relations for common subjects with same action to both verbs (6,12), but again the situation remained ambiguous whenever their logical value towards both verbs was opposite (Table 12.). The situation was slightly better because the first subsets $B1^{(1)}$ and $B1^{(2)}$ had smaller error with affirmative verbs while $B2^{(1)}$ and $B2^{(2)}$ matched whenever the verbs were negative. Lots of problems appeared with the differences between subject subsets and sets (Table 13.). Later was resolved by cross testing of all new object classes with verb from one and subject sets from the other network (Table 14.). In this case question marks in (8) and (10) were replaced by both relations: affirmative and negative. Four remaining ambiguities (7, 9, 11, 13) could not be avoided, so they were again excluded from the set of logical relations.

5. Further research

The main conclusion of the research presented so far is that algorithmic approach in creation of hierarchical networks for two verbs can be successfully replaced by connectionist. But immediately one big problem occurs. Is it possible to embed the information in former smaller networks directly? With other words, is it possible to find such patterns which successfully transform network architecture into desired one, or a completely new network should be trained from the beginning. Unfortunately, it is very hard to imagine that the set of 12 processing units with double noun (NX1 and NX2), object ($A1^{(1)}$, $A2^{(2)}$) and subject ($A2^{(1)}$, $A2^{(2)}$) classes can be transformed to a set with 14 units and single noun, object and subject unit. One question will certainly be the inheritance of former roles. The second one is much more complicated, i.e. how to exclude the obsolete units without damaging the existing connections they produced. It is probably better to forget this idea.

Apart from this first attempt towards automatic network creation several further steps have already been done. Each of three cases was separately trained in corresponding network and then patterns about new sentences were exposed. The number of subject classes from 8 went to 26 (16 intersections, 8+2 differences). Although the amount of object classes was still reasonable (4-6) with such combinatorial explosion it was very difficult to establish any logical relation. Anyway, all legal relations were again adopted as correct and 6 new networks were formed. Again a new sentence was added. With only four sentences common network was supposed to consist of 80 subject units. As first they had to be grouped and joined with related parental classes which augmented the network additionally. At this point the research had to be stopped. Nevertheless, the theorem was always correct.

The only satisfactory fact in network creation and composition is that real sentences contain limited number of nouns appearing as subjects and objects. Furthermore, in one particular context they are frequently repeated without novel logical relations. Therefore, this theoretical research will be applied and practically tested for real corpus.

Appendix A: Relations for equal translations of the source verb

Operation	verb	error	NX1	$A2^{(1)}$	$B1^{(1)}$	$B2^{(1)}$	NX2	$A2^{(2)}$	$B1^{(2)}$	$B2^{(2)}$
$A1^{(1)} \cap A1^{(2)}$	a.	1.2382	27	2	41	1	27	3	41	1
	n.	1.2345	27	2	1	41	27	3	1	41
$A1^{(1)} \setminus A1^{(2)}$	a.	1.4162	-8	-29	42	-6	-19	-20	30	-18
	n.	1.4135	-8	-29	-6	42	-19	-20	-18	30
$A1^{(2)} \setminus A1^{(1)}$	a.	1.4159	-19	-20	30	-18	-8	-29	42	-6
	n.	1.4128	-19	-20	-18	30	-8	-29	-6	42

Table 1. Relations between object sets

Operation	verb	error	NX1	$A1^{(1)}$	$B1^{(1)}$	$B2^{(1)}$	NX2	$A1^{(2)}$	$B1^{(2)}$	$B2^{(2)}$
$B1^{(1)} \cap B1^{(2)}$	a.	1.3819	-23	41	46	10	-23	41	46	10
	n.	5.1881	-25	47	0	59	-25	47	0	59
$B2^{(1)} \cap B1^{(2)}$	a.	1.1880	-23	44	10	51	-21	44	96	-41
	n.	1.1854	-21	44	-41	96	-23	44	52	10
$B1^{(1)} \cap B2^{(2)}$	a.	1.1892	-21	44	96	-41	-23	44	10	51
	n.	1.1853	-23	44	52	10	-21	44	-41	96
$B2^{(1)} \cap B2^{(2)}$	a.	5.1984	-25	47	59	0	-25	47	59	0
	n.	1.3861	-23	41	10	45	-23	41	10	46

Table 2. Intersections between subject sets

Operation	verb	error	NX1	$A1^{(1)}$	$A2^{(1)}$	$B1^{(1)}$	$B2^{(1)}$	NX2	$A1^{(2)}$	$A2^{(2)}$	$B1^{(2)}$	$B2^{(2)}$
$B1^{(1)} \setminus B1^{(2)}$	a.	1.4542	-18	42	-14	119	-21	5	37	-34	-40	-5
	n.	1.2786	-21	42	-10	68	29	3	37	-30	-92	45
$B2^{(1)} \setminus B1^{(2)}$	a.	5.2711	-22	44	-11	84	24	5	39	-34	1	-56
	n.	1.4319	-20	40	-10	32	68	5	35	-31	-47	-5
$B1^{(1)} \setminus B2^{(2)}$	a.	1.4278	-20	40	-10	68	31	5	35	-31	-5	-47
	n.	5.2605	-22	44	-11	24	84	5	39	-35	-56	1
$B2^{(1)} \setminus B2^{(2)}$	a.	1.2814	-21	42	-10	29	68	3	37	-30	45	-92
	n.	1.4501	-18	42	-14	-21	118	5	37	-34	-5	-40

Table 3. Differences between subject subsets from both networks

	$A1^{(1)}$ $A1^{(2)}$				$A1^{(1)}$ $A1^{(2)}$				$A1^{(2)}$ $A1^{(1)}$			
excited units	verb	error	a.	n.	verb	error	a.	n.	verb	error	a.	n.
$B1^{(1)}$ aff. and	a.	1.7812	172	9	a.	1.6563	103	-65	a.	1.6556	103	-65
$B1^{(2)}$ aff.	n.	5.3162	144	50	n.	5.4720	73	-21	n.	5.4707	73	-21
$B1^{(1)}$ aff. and	a.	2.3201	109	75	a.	1.4947	37	3	a.	1.4694	39	1
$B2^{(2)}$ aff.	n.	2.3153	75	109	n.	1.4660	1	39	n.	1.4907	3	37
$B1^{(1)}$ affected	a.	0.8357	131	35	a.	0.8426	61	-38	a.	0.9521	62	-39
	n.	2.4146	96	77	n.	2.5772	24	5	n.	2.7031	24	5
$B1^{(1)}$ aff. and	a.	1.7668	155	-7	a.	1.5976	84	-79	a.	1.8464	86	-81
$A2^{(2)}$ inh.	n.	5.3353	125	31	n.	5.4468	52	-39	n.	5.6912	53	-40

Table 4. Additional testing for logical relations

Appendix B: Relations for one verb with two different translations

Operation	verb	error	NX1	$B1^{(1)}$	$B2^{(1)}$	G1a.	G1n.	NX2	$B1^{(2)}$	$B2^{(2)}$	G2a.	G2n.
$A1^{(1)} \cap A1^{(2)}$	a.	2.0253	27	52	-16	65	47	36	21	21	30	30
	n.	2.0242	27	-16	52	47	65	36	21	21	30	30
$A1^{(1)} \setminus A1^{(2)}$	a.	1.0069	-8	44	-29	34	16	-16	6	6	-10	-10
	n.	1.0079	-8	-29	44	16	34	-16	6	6	-10	-10
$A1^{(2)} \setminus A1^{(1)}$	a.	1.1834	-16	40	-35	26	8	-21	11	11	-2	-2
	n.	1.1821	-16	-35	39	8	26	-21	11	11	-2	-2

Table 5. Relations between object sets for first translation of the verb

Operation	verb	error	$B1^{(1)}$	$B2^{(1)}$	G1a.	G1n.	$B1^{(2)}$	$B2^{(2)}$	G2a.	G2n.
$B1^{(1)} \cap B1^{(2)}$	a.	1.2050	68	-22	75	-13	41	15	43	-32
	n.	3.7901	-1	53	68	2	40	15	44	-31
$B2^{(1)} \cap B1^{(2)}$	a.	3.7892	-1	53	2	68	40	15	44	-31
	n.	1.2082	-23	68	-13	75	41	15	44	-32
$B1^{(1)} \cap B2^{(2)}$	a.	1.2070	68	-23	75	-13	16	41	-32	44
	n.	3.7882	-1	53	68	2	15	40	-31	44
$B2^{(1)} \cap B2^{(2)}$	a.	3.7908	53	-1	2	68	15	40	-31	44
	n.	1.2055	-22	68	-13	75	15	41	-32	43

Table 6. Intersections between subject sets for first translation

Operation	verb	error	NX1	$A1^{(1)}$	$A2^{(1)}$	G1a.	G1n.	NX2	$A1^{(2)}$	$A2^{(2)}$	G2a.	G2n.
$B1^{(1)} \setminus B1^{(2)}$	a.	1.0914	-15	37	-5	64	-19	10	9	-25	-42	33
	n.	3.6182	-18	42	-3	58	-5	9	11	-25	-41	33
$B1^{(1)} \setminus B2^{(2)}$	a.	3.6202	-18	42	-3	-5	58	9	11	-25	-41	33
	n.	1.0895	-15	37	-5	-19	64	10	9	-25	-42	33
$B2^{(1)} \setminus B1^{(2)}$	a.	1.0883	-15	37	-5	64	-19	10	9	-25	33	-42
	n.	3.6191	-18	42	-3	58	-5	9	11	-25	33	-41
$B2^{(1)} \setminus B2^{(2)}$	a.	3.6175	-18	42	-3	-5	58	9	11	-25	33	-41
	n.	1.0912	-15	37	-5	-19	64	10	9	-25	33	-42

Table 7. Differences between subject subsets for first translation of the verb

Operation	verb	error	NX1	$A1^{(1)}$	$A2^{(1)}$	G1a.	G1a.	NX2	$A1^{(2)}$	$A2^{(2)}$	G2a.	G2n.
$B1^{(2)} \setminus B1^{(1)}$	a.	3.5111	0	28	-21	-7	56	-7	23	-11	32	-39
	n.	0.9460	0	26	-18	-21	65	-8	22	-7	34	-38
$B1^{(2)} \setminus B2^{(1)}$	a.	0.9437	0	26	-17	65	-21	-8	22	-7	34	-38
	n.	3.5102	0	28	-21	56	-7	-7	23	-11	32	-39
$B2^{(2)} \setminus B1^{(1)}$	a.	3.5092	0	28	-22	-8	56	-7	23	-11	-39	32
	n.	0.9405	0	26	-18	-21	65	-8	22	-7	-38	33
$B2^{(2)} \setminus B2^{(1)}$	a.	0.9428	0	26	-17	65	-21	-8	22	-7	-38	33
	n.	3.5049	0	28	-21	56	-7	-7	23	-11	-39	32

Table 8. Differences between subject sets for second translation

Operation	verb	error	NX1	$A1^{(1)}$	$A2^{(1)}$	G1a.	G1a.	NX2	$A1^{(2)}$	$A2^{(2)}$	G2a.	G2n.
$B1^{(1)} \setminus A2^{(2)}$	V1a.	1.2389	26	68	-20	85	-4	-52	-52	-52	19	19
	V1n.	3.7873	28	0	54	77	11	-52	-53	-53	19	19
$B2^{(1)} \setminus A2^{(2)}$	V1a.	3.7894	28	54	0	11	77	-52	-53	-53	19	19
	V1n.	1.2396	26	-20	68	-4	85	-52	-52	-52	19	19
$B1^{(2)} \setminus A2^{(1)}$	V2a.	1.2391	-52	-52	-52	19	19	26	68	-20	85	-4
$B2^{(2)} \setminus A2^{(1)}$	V2n.	1.2394	-52	-52	-52	19	19	26	-20	68	-4	85

Table 9. Differences between first subject subsets and second subject set

Operation	verb	error	$A2^{(1)}$	$B1^{(1)}$	$B2^{(1)}$	G1a.	G1n.	$A2^{(2)}$	$B1^{(2)}$	$B2^{(2)}$	G2a.	G2n.
$A1^{(1)} \setminus A1^{(2)}$	V1a.	1.2582	5	37	-33	52	34	11	54	29	50	-23
$B1^{(2)}$ affected	V1n.	1.2599	5	-33	37	34	52	11	54	29	50	-23
$A1^{(1)} \setminus A1^{(2)}$	V1a.	1.2571	5	37	-33	52	34	11	29	54	-23	50
$B2^{(2)}$ affected	V1n.	1.2547	5	-33	37	34	52	11	29	54	-23	50
$A1^{(1)} \setminus A1^{(2)}$	V2a.	1.3132	8	57	32	54	-18	9	34	-36	49	30
$B1^{(1)}$ affected	V2n.	1.3101	8	57	32	54	-18	9	-36	34	30	49
$A1^{(1)} \setminus A1^{(2)}$	V2a.	1.3081	8	32	57	-17	54	9	34	-36	49	30
$B2^{(1)}$ affected	V2n.	1.3112	8	32	57	-18	54	9	-36	34	30	49

Table 10. Establishing logical relations between new classes

Appendix C: Relations for two different verbs

Operation	verb	error	NX1	$B1^{(1)}$	$B2^{(1)}$	G1a.	G1n.	NX2	$B1^{(2)}$	$B2^{(2)}$	G2a.	G2n.
$A1^{(1)} \cap A1^{(2)}$	a.	1.2793	29	49	-2	76	41	26	26	8	9	26
	n.	1.2793	29	-2	49	41	76	26	8	26	26	9
$A1^{(1)} \setminus A1^{(2)}$	a.	1.2163	-5	41	-15	48	13	-18	14	-6	-34	-15
	n.	1.2146	-5	-15	41	13	48	-18	-6	14	-15	-34
$A1^{(2)} \setminus A1^{(1)}$	a.	1.2423	-16	39	-18	37	1	-8	-26	17	-23	-23
	n.	1.2418	-16	-18	39	1	37	-8	17	-26	-3	-3

Table 11. Relations between object sets for the first verb

Operation	verb	error	$B1^{(1)}$	$B2^{(1)}$	G1a.	G1n.	$B1^{(2)}$	$B2^{(2)}$	G2a.	G2n.
$B1^{(1)} \cap B1^{(2)}$	a.	1.1998	70	3	92	-22	50	7	30	-37
	n.	4.3116	16	56	72	41	28	30	54	-63
$B2^{(1)} \cap B1^{(2)}$	a.	1.9038	33	39	33	46	70	-16	2	-14
	n.	1.2049	-26	91	1	72	51	8	28	-37
$B1^{(1)} \cap B2^{(2)}$	a.	1.2066	91	-26	71	1	8	51	-37	28
	n.	1.8999	39	33	46	33	-17	70	-14	3
$B2^{(1)} \cap B2^{(2)}$	a.	4.3193	56	16	11	72	30	28	-63	54
	n.	1.2010	-3	70	-23	92	7	50	-37	30

Table 12. Intersections between subject subsets for the first verb

Operation	verb	error	NX1	$A1^{(1)}$	$A2^{(1)}$	G1a.	G1a.	NX2	$A1^{(2)}$	$A2^{(2)}$	G2a.	G2n.
$B1^{(1)} \setminus B1^{(2)}$	V1a.	1.1811	-16	44	-14	66	0	5	33	-33	-55	13
$B1^{(1)} \setminus B2^{(2)}$	V1n.	1.0633	-17	43	-11	-24	87	5	31	-32	-52	12
$B1^{(1)} \setminus A2^{(2)}$	V1a.	1.1079	-6	11	12	90	-2	-47	25	-55	11	9
$B2^{(2)} \setminus B1^{(1)}$	V1a.	1.0641	-17	43	-11	87	-24	5	32	-32	12	-52
$B2^{(2)} \setminus B2^{(1)}$	V1n.	1.1822	-16	44	-14	0	66	5	33	-33	13	-55
$B2^{(2)} \setminus A2^{(1)}$	V1n.	1.1075	-6	12	-11	-2	90	-47	-55	25	9	11

Table 13. Correct differences between subject subsets and sets

Operation	verb	error	$A2^{(1)}$	$B1^{(1)}$	$B2^{(1)}$	G1a.	G1n.	$A2^{(2)}$	$B1^{(2)}$	$B2^{(2)}$	G2a.	G2n.
$A1^{(1)} \cap A1^{(2)}$	V1a.	1.0827	5	31	0	84	33	20	76	15	47	3
$B1^{(2)}$ affected	V1n.	1.9927	4	0	52	54	68	21	60	34	66	-16
$A1^{(1)} \cap A1^{(2)}$	V1a.	1.9949	4	-22	-22	68	54	21	34	60	-16	66
$B2^{(2)}$ affected	V1n.	1.0833	5	52	31	33	84	20	15	76	3	47
$A1^{(1)} \cap A1^{(2)}$	V2a.	1.0809	20	76	15	47	3	5	31	0	84	33
$B1^{(1)}$ affected	V2n.	1.9935	21	60	34	66	-16	4	0	52	54	68
$A1^{(1)} \cap A1^{(2)}$	V2a.	1.9932	21	34	60	-16	66	4	-22	-22	68	54
$B2^{(1)}$ affected	V2n.	1.0844	20	15	76	3	47	5	52	31	33	84
$A1^{(1)} \setminus A1^{(2)}$	V1a.	0.4241	-8	27	-7	71	19	9	71	8	25	-17
$B1^{(2)}$ affected	V1n.	1.3896	-8	-29	48	40	54	10	54	28	46	-37
$A1^{(1)} \setminus A1^{(2)}$	V1a.	1.3924	-8	48	-29	54	40	10	28	54	-38	46
$B2^{(2)}$ affected	V1n.	0.4237	-8	-7	27	19	71	9	8	71	-17	25
$A1^{(1)} \setminus A1^{(2)}$	V2a.	0.4182	6	72	9	30	-10	-6	26	-9	65	13
$B1^{(1)}$ affected	V2n.	1.3859	7	55	30	52	-32	-6	-30	47	34	48
$A1^{(1)} \setminus A1^{(2)}$	V2a.	1.3882	7	30	55	-32	52	-6	47	-30	48	34
$B2^{(1)}$ affected	V2n.	0.4204	7	9	71	-11	31	-6	-9	26	13	65

Table 14. Establishing logical relations between new classes

R E F E R E N C E S

[1] Berard-Dugourd A., Fragues J., Landau M.C., Rogala J.P.: A Text Analysis and Query/Answer System on Conceptual Graphs, in Conceptual Graphs for Semantics and Deduction, ed. by J.Fargues, ACAI-89 Distribution Draft, 1989

[2] Čundeva K.: Semantic Network Representation of Bilingual Dictionary, in Proceedings of 13th International Conference on Information Technology Interface, Cavtat, 10-14 June, 1991, pp. 187-194

[3] Čundeva K.: Machine Translation System Realised by Neural Networks, PhD Thesis, University Saint Kiril and Metodij, Skopje, 1993

[4] Čundeva K.: Learning in Example-Based Machine Translation, in Proceedings of 15th International Conference on Information Technology Interface, Pula, 15-18 June, 1993, pp. 207-212

[5] Čundeva K.: Connectionism in Machine Translation of Macedonian and English Prepositions, in Proceedings of the Second Turkish Symposium on Artifical Intelligence and Artifical Neural Networks, Istanbul, 24-25 June 1993, pp. 146-153

[6] EDR Techical Report "An Overiew of the EDR Electronic Dictionaries", Japan Electronic Dictionary Research Institute, TR-024., 1990

[7] Hutchins W.J., Somers H.L.: An Introduction to Machine Translation, Academic Press, New York, 1992

[8] Koneski B.: Grammar of Macedonian Literary Language, Kultura, Skopje, 1987

[9] Parker F.: Linguistics for non-linguists, Taylor & Francis LTD, London, 1986

ХИЕРАРХИСКИ СТРУКТУРИ

КОНЕКЦИОНИЗАМ НАСПРОТИ ДЕТЕРМИНИЗАМ

Катерина Чундева

Р е з и м е

Архитектурата на невронските мрежи користени кај конекционистичкиот систем за машинско преведување беше одредена од хиерархиските маркери. Маркерите беа користени за кодирање на основните зборови во речникот. Создавањето на хиерархиските структури од кои што маркерите беа изведени имаше наполно алгоритамски карактер. Во овој труд се прикажани обиди детерминистичкиот приод да се замени со конекционистичкиот.

Prirodno-matematički fakultet
Institut za informatika
p.f. 162, 91000 Skopje
Macedonia