A LEXICON OF DISTRIBUTED NOUN REPRESENTATIONS CONSTRUCTED BY TAXONOMIC TRAVERSAL

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1 INTRODUCTION

In order to construct systems which can process natural language in a sophisticated fashion it is highly desirable to be able to represent linguistic meanings in a computationally tractable fashion. One approach to the problem of capturing meanings at the lexical level is to use a form of distributed representation where each word meaning is converted into a point in an n -dimensional space (Sutcliffe, 1992a). Such representations can capture a wide variety of word meanings within the same formalism. In addition they can be used within distributed representations for capturing higher level information such as that expressed by sentences (Sutcliffe, 1991a). Moreover, they can be scaled to suit a particular tradeoff of specificity and memory usage (Sutcliffe, 1991b). Finally, distributed representations can be processed conveniently by vector processing methods or connectionist algorithms and can be used either as part of a symbolic system (Sutcliffe, 1992b) or within a connectionist architecture (Sutcliffe, 1988). In previous work we have shown how such representations can be constructed automatically by the method of taxonomic traversal, using the Merriam Webster Compact Electronic dictionary (Sutcliffe, 1993) and the Irish-Irish An Foclóir Beag (Sutcliffe, McElligott and Ó Néill, 1993). However our efforts so far have been limited by our parsing technology to lexicons of a few thousand words. We describe here how we can generate a lexical entry for any of the 71,000 nouns² in the Princeton WordNet (Beckwith, Fellbaum, Gross and Miller, 1992), and the initial tests we have conducted on the representations.

Our method is closely related to other work which exploits the taxonomic nature of dictionary definitions (Amsler, 1980; Hiedorn, Byrd and Chodorow, 1986; Vossen, 1990; Guthrie, Slator, Wilks and Bruce, 1990; Nutter, Fox and Evens, 1990). In addition there have already been some very interesting approaches to the construction of distributed semantic representations either from dictionaries (Wilks et al., 1990) or from corpora (Schuetze, 1993).

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²This figure includes hyphenated terms, compound nouns and proper names.

2 EXTRACTING FEATURE REPRESENTATIONS

The object of our work is to produce for each noun-sense in a lexicon a semantic representation consisting of a set of feature-centrality pairs. The features are semantic attributes each of which says something about the concept being defined. The centrality associated with each feature is a real number which indicates how strongly the feature contributes to the meaning of the concept. The use of centralities allows us to distinguish between important and less important features in a semantic representation. By scaling the centralities in a particular noun-sense representation so that the sum of their squares is one we can use the dot product operation to compute the semantic similarity of a pair of concepts. A word compared to itself always scores one while a word compared to another word is always less than or equal to one. This is equivalent to saying that each word representation is a vector of length one in an n -dimensional space, where n is the number of features which are used in the lexicon as a whole.

Our algorithm for constructing the representations is based on two well-known observations. Firstly, a word definition in a dictionary provides attribute information about the concept ('a mastiff is a LARGE dog'). Secondly a word definition also provides taxonomic information about the concept ('a mastiff is a large DOG'). We use the former to derive attributes for our representation, and the latter to obtain other definitions higher up in the taxonomy from which further attributes can be obtained. In assigning centralities to features, we use the same value for each attribute added at a particular level in the taxonomic hierarchy, and we reduce the value used as we move up to higher levels. This corresponds to the intuition that a feature which is derived from a definition which is close to the word of interest in the taxonomy contributes more to its meaning than one which is derived from a more distant definition.

The Princeton WordNet is very suitable for use in implementing our extraction algorithm because taxonomic links are represented explicitly by pointers. In most MRDs such links have to be deduced by syntactic and semantic analysis of sense definitions. Nouns in WordNet are organised around *synsets*. Each synset may include a list of synonyms, pointers to hyponym and hypernym synsets, and a gloss corresponding to a conventional dictionary definition.

Figure 1. Synset Hierarchy for the word 'terrier' derived from Princeton Wordnet.

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1 sense of terrier

Sense 1
terrier --
  (any of several usu. small short-bodied breeds originally trained
   to hunt animals living underground)

=> hunting dog --
  (a dog used in hunting game)

=> domestic dog, pooch, Canis familiaris --
  (domesticated mammal prob. descended from the common wolf; occurs in
   many breeds)

=> dog

=> canine, canid --
  (any of various fissiped mammals with nonretractile claws and
   typically long muzzles)

=> carnivore --
  (terrestrial or aquatic flesh-eating mammal; terrestrial carnivores
   have four or five clawed digits on each limb)

=> placental mammal, eutherian, eutherian mammal

=> mammal --
  (any warm-blooded vertebrate that nourish their young with milk
   and having the skin more or less covered with hair; young are
   born alive except for the small subclass of monotremes)

=> vertebrate, craniate --
  (animals having a bony or cartilagenous skeleton with a
   segmented spinal column and a large brain enclosed in a skull
   or cranium)

=> chordate

=> animal, animate being, beast, brute, creature, fauna --
  (a living organism characterized by voluntary movement)

=> life form, organism, being, living thing --
  (any living entity)

=> entity --
  (something having concrete existence; living or nonliving)
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Table 1. Twenty words in five categories				
cars	dogs	flowers	trees	people
chariot	pug	pansy	larch	bruiser
motorbike	terrier	daffodil	pine	patriarch
jeep	lapdog	tulip	oak	siren
moped	chihuahua	rose	sycamore	rake

The extraction algorithm starts with the synset corresponding to the word-sense for which we wish to create a lexical entry. The gloss is tokenised, function words are removed and the remaining content words are converted to their root inflection. All such words are considered to be features of the word-sense, and are given a centrality of 1.0. We then chain upwards using a hypernymic link (if any)³. At the next level up, features are extracted from the hypernym's gloss, using a centrality of 0.9. The process is repeated, reducing the centrality by 0.1 at each level, until either the top of the hierarchy is reached or the centrality falls to zero. Finally, the representation, consisting of a set of feature-centrality pairs, is normalised.

3 RESULTS

The algorithm described above has been implemented and can be used to construct a lexical entry for any of the nouns in the WordNet database. Figure 1 shows the synset hypernym hierarchy for the word 'terrier' in WordNet. Figure 2 shows the semantic representation derived by the algorithm for this word. We present here some preliminary experiments which attempt to measure the performance of the lexicon. Four words were chosen from each of five categories of noun which we label cars, dogs, flowers, trees and people. These are shown in Table 1. Table 2 shows a summary of the characteristics of the word representations in the set of twenty words. Pairs of categories were chosen, cars-dogs, flowers-trees and so on, each containing eight words. A series of eight-by-eight tables was then computed, showing the dot product of each word with every other word in the category pair. Table 3 shows the results for the cars-dogs matrix. There are several points to note about this table. Firstly, the match of one car word with another is high, ranging between 0.58 and 1.0 with an average of 0.8. This shows that the lexicon has captured the similarity between the car concepts. Secondly, the match of one dog word with another is also high, ranging between 0.63 and 1.0 with an average of 0.76, for the same reason. Thirdly, the match of a car word with a dog word is low, ranging between 0.05 and 0.17 with an average of 0.1. This is because cars and dogs are not closely linked semantically. Table 4 shows results for the flowers-trees matrix. Flowers and trees are much more closely related semantically than cars and dogs, and this is reflected in the results. Flower words match with tree words in a range of 0.30 to 0.67

³At present we only choose the first such link if there are several.

Table 2. Lexical Representation Summary	
No of words	20
Total number of features	249
Average number of features	39
Minimum	17
Maximum	76

with an average of 0.4, much higher than for cars and dogs. The match of flowers with flowers or trees with trees continues to be high. Finally, Table 5 shows the people-dogs matrix. Note here that the match of people with themselves is lower than that of dogs with themselves (average 0.63 rather than average 0.76.) This is because the people words are in fact a rather disparate set. Note in particular that 'bruiser' against 'rake' is the best match while 'bruiser' against 'patriarch' is the worst. This matches one's intuitions about these concepts: patriarchs are "good" while 'bruisers' and 'rakes' are not.

4 CONCLUSIONS

We have presented a simple algorithm which allows a set of distributed lexical semantic representations to be constructed from nouns in the Princeton WordNet. The results show that the method works and produces good results. The main reason for this is the explicit taxonomic information in WordNet which has to be inferred in other dictionaries. Incorrect taxonomic information seriously degrades the performance of this kind of method. On the other hand errors in individual features are not so harmful as they have no knock-on effects. However, we are engaged in eliminating errors in word sense and syntactic category which are the principal sources of inaccuracy in the method. In addition we are working on objective methods for measuring the performance of the lexicon on a large scale.

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Table 3. Cars vs. Dogs								
	chariot	motorbike	jeep	moped	pug	terrier	lapdog	chihuahua
chariot	1.00	0.74	0.58	0.73	0.13	0.17	0.14	0.09
motorbike	0.74	1.00	0.69	1.00	0.11	0.11	0.11	0.06
jeep	0.58	0.69	1.00	0.68	0.08	0.09	0.09	0.05
moped	0.73	1.00	0.68	1.00	0.10	0.10	0.11	0.05
pug	0.13	0.11	0.08	0.10	1.00	0.68	0.65	0.69
terrier	0.17	0.11	0.09	0.10	0.68	1.00	0.63	0.72
lapdog	0.14	0.11	0.09	0.11	0.65	0.63	1.00	0.67
chihuahua	0.09	0.06	0.05	0.05	0.69	0.72	0.67	1.00

Table 4. Flowers vs. Trees								
	pansy	daffodil	tulip	rose	larch	pine	oak	sycamore
pansy	1.00	0.32	0.36	0.49	0.37	0.32	0.37	0.28
daffodil	0.32	1.00	0.70	0.37	0.38	0.33	0.37	0.39
tulip	0.36	0.70	1.00	0.41	0.39	0.33	0.37	0.30
rose	0.49	0.37	0.41	1.00	0.56	0.58	0.67	0.44
larch	0.37	0.38	0.39	0.56	1.00	0.83	0.74	0.64
pine	0.32	0.33	0.33	0.58	0.83	1.00	0.83	0.62
oak	0.37	0.37	0.37	0.67	0.74	0.83	1.00	0.60
sycamore	0.28	0.39	0.30	0.44	0.64	0.62	0.60	1.00

Table 5: People vs. Dogs								
	bruiser	patriarch	siren	rake	pug	terrier	lapdog	chihuahua
bruiser	1.00	0.40	0.52	0.63	0.12	0.15	0.13	0.08
patriarch	0.40	1.00	0.40	0.55	0.15	0.18	0.16	0.17
siren	0.52	0.40	1.00	0.50	0.14	0.17	0.14	0.09
rake	0.63	0.55	0.50	1.00	0.12	0.15	0.13	0.08
pug	0.12	0.15	0.14	0.12	1.00	0.68	0.65	0.69
terrier	0.15	0.18	0.17	0.15	0.68	1.00	0.63	0.72
lapdog	0.13	0.16	0.14	0.13	0.65	0.63	1.00	0.67
chihuahua	0.08	0.17	0.09	0.08	0.69	0.72	0.67	1.00

repn(terrier, '(any of several usu. small short-bodied breeds originally trained to
 hunt animals living underground)', [[any, 0.19], [several, 0.19], [small, 0.19],
 [breed, 0.19], [originally, 0.19], [trained, 0.19], [hunt, 0.19], [animal, 1.9], [living,
 0.19], [underground, 0.19], [a, 0.17], [dog, 0.17], [used, 0.17], [in, 0.17],
 [hunting, 0.17], [game, 0.17], [domesticated, 0.15], [mammal, 0.15], [descend, 0.15],
 [common, 0.15], [wolf, 0.15], [occur, 0.15], [many, 0.15], [various, 0.11], [fissiped,
 0.11], [with, 0.11], [nonretractile, 0.11], [claw, 0.11], [typically, 0.11], [long,
 0.11], [muzzle, 0.11], [terrestrial, 0.096], [aquatic, 0.096], ['flesh-eating', 0.096],
 [carnivore, 0.096], [have, 0.096], [four, 0.096], [five, 0.096], [clawed, 0.096],
 [digit, 0.096], [on, 0.096], [each, 0.096], [limb, 0.096], ['warm-blooded', 0.057],
 [vertebrate, 0.057], [nourish, 0.057], [young, 0.057], [milk, 0.057], [skin, 0.057],
 [more, 0.057], [less, 0.057], [covered, 0.057], [hair, 0.057], [are, 0.057], [born,
 0.057], [alive, 0.057], [except, 0.057], [monotreme, 0.057], [bony, 0.038], [skeleton,
 0.038], [segment, 0.038], [spinal, 0.038], [column, 0.038], [large, 0.038], [brain,
 0.038], [enclosed, 0.038], [skull, 0.038], [cranium, 0.038], [organism, 0.01],
 [characterized, 0.01], [voluntary, 0.01], [movement, 0.01], [entity, 0.01], [concrete,
 0.01], [existence, 0.01], [nonliving, 0.01]]).

Figure 2. The semantic representation for 'terrier' produced by the algorithm.

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Table 6 Word-Word Summary

Cars-Cars average	0.80
Cars-Dogs average	0.10
Dogs-Dogs average	0.76
Flowers-Flowers average	0.58
Trees-Flowers average	0.40
Trees-Trees average	0.78
People-People average	0.63
Dogs-Dogs average	0.76
People-Dogs average	0.14