With raised eyebrows or the eyebrows raised? A Neural Network Approach to Grammar Checking for Definiteness*

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Abstract  

In this paper, we use a feature model of the semantics of plural determiners to present an approach to grammar checking for definiteness. Using neural network techniques, a semantics – morphological category mapping was learned. We then applied a textual encoding technique to the 125 occurrences of the relevant category in a 10 000 word narrative text and learned a surface – semantics mapping. By applying the learned generation function to the newly generated representations, we achieved a correct category assignment in many cases (87%). These results are considerably better than a direct surface categorization approach (54 %), with a baseline (always guessing the dominant category) of 60 %. It is discussed, how these results could be used in multilingual NLP applications.

1 Introduction  

Most uses of the definiteness category in English are grammatically constrained, i.e. a substitution of a definite for an indefinite determiner and vice versa leads to ungrammatical sentences. In this paper, we use a model of the semantics of plural determiners to present an approach to automatic generation of the correct determiner. We have identified a set of semantic features for the description of relevant meanings of plural definiteness. A small training set (30 sentences) was

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created according to linguistic criteria, and a functional mapping from the semantic feature representation to the overt category of indefinite/definite article was learned using neural network techniques. We have then provided a surface-oriented textual encoding of a 10000 word text corpus. We removed the target category in each relevant plural noun occurrence, and automatically generated semantic representations from the encoded text. Because texts are semantically underdetermined, and the text encoding technique involves a further huge reduction of information content, these representations have some degree of noise. However, in generation we can assign the correct category in many cases (87%). These results are put into perspective with experiments on surface categorization of sentences, i.e. applying learning techniques without the benefit of semantic representations.

The basic methodology in designing a semantic feature representation consists in finding a set of semantic dimensions which correspond to the logical distinctions expressed by a certain grammatical category (cf. [Kamp and Reyle, 1993, Link, 1991a, Link, 1991b, Scheler, 1996]). In the case of definite determiners, we have chosen the dimensions of givenness (i.e. type of anaphoric relation), of quantification, of type of reference (i.e. predication or denotation), of boundedness (i.e. mass reference or individual reference), and of collective agency. The different logical forms of the sentences can be represented by a set of sentential operators, which are defined in first-order logic. These sentential operators can be used as atomic semantic features, which are consequently sufficient in representing the logical meaning of a sentence with respect to the chosen semantic dimensions. This approach is significantly different from POS or sense-tagging systems such as [Yarowsky, 1992, Schmid, 1994, Brill, 1993, Church, 1988, Jelinek, 1985]. A complete list of semantic features and dimensions is given in the appendix. A semantic feature set is sufficient for the explanation of a given morphological category if it is possible to generate this category from the corresponding feature representation.

The paper is structured as follows: First, we present an experiment in learning a generation function, i.e. a mapping from semantic representations to surface categories. Then we explain the principles of textual coding that we have used for the semantic feature extraction experiments. Finally, we show how these mapping functions can be combined to provide a grammar checker for the definiteness category of English, and discuss possible applications in multilingual NLP.

2 From semantic features to morphological expression

The question that has been investigated by the first experiment is the adequacy of a semantic representation for noun phrases which consists of the semantic di-
mensions and individual features given in the appendix. In particular, we wanted to know how a functional assignment that has been learned by a set of linguistically chosen examples carries over to instances of the relevant phenomenon in real texts.

2.1 Method

In order to answer this question, we use a connectionist method of supervised learning ("quickprop" [Fahlman, 1988], a variant of the back-propagation algorithm), as implemented in the SNNS-system (cf. [Zell and others, 1993]). Supervised learning requires to set up a number of training examples, i.e. cases, where both input and output of a function are given. From these examples a mapping function is created, which generalizes to new patterns of the same kind.

We created a small training corpus for typical occurrences of bare plurals and definite plurals. Grammars written for second language learning often provide a good possibility of obtaining a small sample of individual sentences, designed to cover all possible uses of a specific category in discourse. 30 example sentences with distinct feature representations were adapted from [Thompson and Martinet, 1969]. For these examples, semantic feature representation were created by hand. Neutral values (*) were also included. Inter-subject agreement of tagging of the data was 94% for two subjects (myself and a student). I.e. there was disagreement for 37 tags (out of 625), most of which (22) concerned the category of anaphoric relation.

In principle, there is a better measure of judging the correctness of the feature representation, as each of these features refers to the logical interpretation of the sentence. This means that the feature representation can serve as an intermediate step in creating a cognitive representation expressed in first-order logic, in the same way as it has been realized in [Scheler and Schumann, 1993] for aspectual categories. Correctness may then be tested by creating a set of inferences for each sentence. However, this work is only experimental at present, and has not been performed for definite and indefinite noun phrases yet. Finally, the value of the chosen feature set and individual representations becomes apparent, when we use these representations in the chosen task of generating correct determiners for deliberately truncated (i.e. minus the value for the target category) sentences.

The symbolic descriptions were translated into binary patterns using 1-of-n coding. The assignment of the correct output category consisted in a binary decision, namely, definite plural or bare (indefinite) plural.

We wanted to know how such a set of training examples relates to the patterns found in real texts. Accordingly, we tested the acquired classification on a narrative text, ("Cards on the table" by A. Christie), for which the first 5 chapters were taken, with a total of 9332 words. Every occurrence of a plural noun without a possessive or demonstrative pronoun formed part of the dataset. Modification by a possessive pronoun (my friends), or a demonstrative pronoun (those
He gives wonderful PARTIES.
new general predication pieces *
indef
The MUSICIANS are practicing a new piece.
given all reference pieces collective
def
They were discussing BOOKS and the theater.
new general predicative mass *
indef

Table 1: Examples from the training set: Sentences, semantic representations, and grammatical category

people) leads to a neutralization of the indefiniteness/definiteness distinction as expressed by a determiner. Generating possessive or demonstrative pronouns is beyond the goals of this research. As a result, there were 125 instances of definite or bare plural nouns. Of these, 75 instances had no determiner (the dominant category), and 50 instances had the determiner “the”. This provides a baseline of guessing at 60%. For the text cases, another set of semantic representations was manually created.

2.2 Results

The mapping from semantics to grammatical category for the example sentences could be learned perfectly, i.e. any semantic representation was assigned its correct surface category.

The learned classifier was then applied to the cases derived from the running text. A high percentage of correctness (97 %) could be achieved (cf. Table 2).

This result is remarkable, as it involves a generalization from linguistically selected, ‘made-up’ examples to real textual occurrences. We may assume that the selected set of semantic features describes the relevant semantic dimensions of the surface category of definiteness. We also examined the few remaining misclassifications (cf. Table 3). They are due to stylistic peculiarities, as in 45 and 89. Also, two sentences involving numerals were not classified correctly. This has probably not been sufficiently covered by the training set.

We have achieved to learn a generation function from semantic representations with remarkably few wrong assignments. The remaining problems with functional assignment which are due to stylistic variation are less than we expected, but they may go beyond an analysis in terms of semantic-logical features.
Table 2: Mapping from semantic representation to output category

| INTRODUCTIONS | he gravitated naturally to the side of Colonel Race. |
|---------------|-----------------------------------------------------|
| given all predication mass collective | |
| indef | |
| I held the most beautiful CARDS yesterday. | |
| new some predication pieces | |
| def | |
| He saw four EXPRESSIONS break up - waver. | |
| implied num predication pieces distributive | |
| indef | |
| Yes. That's to say, I passed quite near him THREE TIMES. | |
| implied num predication pieces | |
| indef | |

Table 3: Misclassifications of the text cases

3 Semantic feature extraction from Text

For the goal of cognitive modeling it is interesting to look at the kind of semantic representations necessary to explain attested morphological categories and their use. For practical purposes, however, semantic representations cannot be manually created. They have to be derived from running text by automatic methods. This is a goal that is not easy to reach.

First of all, texts are semantically underdetermined. They do not contain all the information present in a speaker’s mind that corresponds to a full logical representation. Fortunately, these logical representations are often redundant for the selection of a grammatical category, so that a noisy representation may be sufficient for practical NLP tasks such as text understanding, machine translation or grammar checking. Secondly, there remains the problem of how to represent
or code a text such as to derive a maximum of semantic information from it, but reduce its overall information content, which puts too much burden on any current learning technique (in particular the large amount of different lexical words).

In this paper we wanted to look at the possibility of using a neural network learning approach to syntax-semantics mapping for grammar checking, i.e. the automatic correction of the definiteness category in a running text. This could be a valuable feature in a foreign language editor, it is also a significant part of any translation system.

### 3.1 Text Encoding

The text encoding technique should have two important properties:

- reducing the informational content of a text without losing its essential parts for the task at hand
- using only readily accessible surface information, and limiting pre-processing to a minimum

For the former goal we have provided representations using essentially two syntactic schemas:

- $NP - predicate - NP$
- $NP - preposition - NP$

This is a fairly radical approach in reducing syntactic complexity, and it is possible that more detailed representations of syntactic relations would prove an asset in semantic feature extraction. (alternative approaches to text encoding are contained in [Bauer, 1995] and [Scheler, 1994]). However the advantage of this simplistic scheme is that we can use a single fixed-length slot-value representation which fits the local context of most noun phrases. The diversity of lexical items has been reduced by substituting each lexical word by high-level syntactic-semantic features as derived from WordNet [Miller and others, 1993]. Functional words and morphology have been reduced to singular/plural and definite/indefinite distinctions. The full textual encoding scheme looks as follows:

1. head noun
2. adjectival/adverbial modifiers
3. number (singular/plural)
4. definiteness (indef/def or qu)
5. predicate or preposition
6. dependent noun
3 VOICES drawled or murmured.
perceptual_entity * plural qu action * * * *

4 in aid of the London HOSPITALS.
event * singular indef prep institution desc_adj plural qu

5 a Lovely Young Thing with tight poodle CURLS.
object desc_adj singular indef prep body_part desc_adj plural qu

7 He wore a moustache with stiff waxed ENDS.
body_part * singular indef prep part desc_adj plural qu

Table 4: Examples for surface textual coding

7. adjectival/adverbial modifiers
8. number (singular/plural)
9. definiteness (indef/def or qu)

Values in the slots are lexical classes for head noun, predicate and dependent noun (e.g., perceptual_entity, physical_object, body_part, person, communication) and grammatical classes for modifiers (e.g., adjective, numeral, demonstrative). The difficult problem of word sense ambiguity which arises even on the level of primary lexical classes, or syntactic-semantic features, was circumvented by assigning the most frequent lexical class to a lexical word, measured in terms of its different word senses. An easy alternative, namely using all lexical classes in a distributed lexical encoding, was not explored here. Some examples are given in Table 4.

Using 1-of-n coding, we get 53 bits (i.e. 53 features) in 9 slots. We constructed another neural network with a 53-20-15 architecture (input-hidden-output layer), where 20 hidden units proved to be optimal for the given problem, and tried to learn a mapping function from the surface encoding to the semantic layer (15 features).

3.2 Experiments

In order to investigate the possibilities of grammar checking, we left out the definiteness category for the target noun phrase, i.e. substituted indef/def by qu for a single noun phrase per sentence.

We have used crossvalidation by leaving-one-out for the 125 cases. The number of examples is still fairly small for surface-semantics mapping, accordingly we had to use the strong reduction in information outlined above to have a noticeable generalization effect. In some cases the resulting textual representations
look alike, although there are differences in semantic content, which is a major problem for the learning technique used. A learning technique which would be less sensitive to conflicting data would probably improve the performance. The results for learning and for generalization have been split up for the number of errors per pattern. They are given in Table 5.

Table 5: Mapping from encoded surface text to semantic representation

| Learning correct | ≤ 2 errors | ≤ 4 Generalization | > 4 errors |
|------------------|------------|--------------------|------------|
| 100%             | 92%        | 45%                | 35%        |
| 115              | 57         | 43                 | 15         |

These results amount in a total average of 2.73 errors per pattern, where 15 bits had to be set. Our main goal was to generate a set of semantic feature representations from sentences without target categories, and test how much noise the previously learned generation function can tolerate.

4 Grammar checking for determiners

We have observed before that most uses of plural determiners in English are grammatically constrained, and in many cases these grammatical constraints are evident even from single sentences, without further textual context.

4.1 Method

In order to qualify whether a specific use of a determiner is sententially constrained, we have given the list of 125 sentences with the target categories changed to three native speakers. We found that speakers agreed on a core of 15 sentences which were considered acceptable with the opposite category, and received a total of 22 sentences which at least one speaker judged grammatical. This means, in 103 out of the 125 plural noun occurrences, speakers of English seem to have no choice in the use of the determiner. By excluding the 22 sentences with ‘free variation’ we bypass problems of textual coreference and anaphora, which also play an important role in determiner selection (cf. [Aone and Bennett, 1996], ...
Connolly et al., 1995] for learning approaches to anaphora resolution). Still the number of text cases that are narrowly sententially constrained is fairly high. For the remaining cases, we took the generalized semantic representations from the previous experiment, and tested the performance with the learned generation function.

4.2 Results

The results were encouraging: In many cases (89, i.e. 87 %) the system made the correct binary choice. Note that these are generation data on representations that were derived from unseen, only surface-encoded text. When we look at the relation between error per pattern and generation performance (cf. Table 6), a clear picture emerges. While the generation function is fault-tolerant to a degree (app. ≤ 2 errors), its performance decreases when the number of errors per pattern exceeds a certain limit (> 2 errors), up to a point, when we can only reproduce chance level (> 4 errors).

![Graph showing the relationship between correctness of generation and number of errors per pattern]

Table 6: Generation from automatically derived semantic representations

We may also compare this approach to a direct textual categorization approach. In this case we used the textual encoding (53 bits) and tried to learn the morphological category by direct supervised learning. I.e. instead of the 53-20-15 net for semantic feature extraction, coupled by a 15-5-2 net for generation, we used a single 53-X-2 net (where X was optimal at 10) and repeated the learning process for the 103 examples. The results were significantly worse, they did not exceed chance level (cf. Table 7). Including extra hidden layers for automatic construction of a “semantic layer”, i.e. a 53-20-10-15 net, did not significantly improve these results (58/56%).
The main task of this paper has been to identify a set of semantic features for the description of the definiteness category in English and apply it to instances of plural nouns in a real text. An application to grammar checking has been spelled out in the former section. The results lead us to expect that with the development of a more sophisticated textual coding, we may have a practical tool for checking and correcting definiteness of English plural nouns.

The work reported here can also be used for multilingual interpretation and generation. This is especially interesting for languages without nominal determiners, such as Japanese or Russian. In these cases other grammatical information that is provided in the surface coding, e.g. Japanese particles with topic/comment contrast combining the agentive/givenness dimensions and Japanese word order and nominal classifiers, can be used to set the semantic features of the intermediate, interlingual representation (cf. [Wada, 1994]). Generation of an English determiner can then be handled by the unilingual learned generation function.

The history of machine translation and text understanding has shown that mere surface scanning and textual matching approaches tend to level off as they have no capacity for improving performance beyond that of the statistical data analysis tool [Nirenburg et al., 1992]. In contrast, using explicit semantic representations which can be linked to cognitive models provides a basis for both human language understanding and practical NLP. Flat surface analysis may perform much better with huge data sets and less information reduction. Still, using semantic representations has additional advantages for interactive systems both for grammar checking and machine translation. The additional plane of semantic representation allows a system to assess the validity of a given decision and frame a question in other cases.

In order for the envisaged system to have real practical use two kinds of additions are necessary (in addition to the general task of improving the performance

Table 7: Determiner Selection as Classification of Surface Sentences

5 Applications in Multilingual NLP
of the classifier):

- a textual encoding scheme that incorporates a method for coreference resolution to set features in the dimension of anaphoric meaning reliably
- a confidence measure for the proposed determiner, which would make a remaining margin of error tolerable to a user.

The confidence measure could be composed of a value for the generation component which would depend on the completeness of the semantic representation, and a value for the analysis component, which would code the availability of textual features and the probability values of the semantic feature assignment (e.g. 0.9 or 0.6 “collective” etc.).

With these improvements the system could be a useful tool for anyone who uses a foreign language and encounters frequent doubts of grammatical correctness which no written grammar can answer: * “He answered me with the raised eyebrows” is incorrect, but “with raised eyebrows” or “with the eyebrows raised in a mocking twist” is fine.

## A Appendix: Semantic dimensions and features

### A.1 Generalized quantification

1. **num** quantifier with an explicit quantity, e.g. four, five etc.
2. **unique** a plural object may also be unique, for instance, *the arts, the London hospitals* This is possible when it has a *collective* identity (s.below).
3. **some** an unspecified quantity, which constitutes a small percentage
4. **most** an unspecified quantity, which constitutes a large percentage
5. **all** universal quantification, constrained with respect to the discourse setting
6. **general** universal quantification, unconstrained with respect to discourse, but pragmatically constrained

### A.2 Anaphoric relation

7. **given** noun phrase with a co-referring antecedent
8. **implied** noun phrase which refers to an object implied by a lexical relation
9. **new** noun phrase that introduces a new referent
3. Reference to Discourse Objects

10. **denotation** noun phrase that denotes an object term in discourse (e.g., *He was walking about in the park*)

11. **predication** noun phrase that denotes a property in discourse (where a property is a one-place relation of a discourse object) (e.g., *It’s more a park than a garden*)

4. Boundedness

12. **mass** reference to an unbounded quantity of one kind (e.g., *a Lovely Young Thing with tight poodle CURLS*)

13. **pieces** reference to a collection of individuals (e.g., *Those dreadful policewomen in funny HATS who bother people in parks!*)

5. Agentive involvement

14. **collective** a plural noun referring to set of individuals and a common action (e.g., *The two girls sang a duet.*)

15. **distributive** a plural noun referring to a set of objects and individual actions (e.g., *Four people brought a salad to the party.*)

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