Identifying Named Entities in Text Databases from the Natural History Domain

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Abstract

In this paper, we investigate whether it is possible to bootstrap a named entity tagger for textual databases by exploiting the database structure to automatically generate domain and database-specific gazetteer lists. We compare three tagging strategies: (i) using the extracted gazetteers in a look-up tagger, (ii) using the gazetteers to automatically extract training data to train a database-specific tagger, and (iii) using a generic named entity tagger. Our results suggest that automatically built gazetteers in combination with a look-up tagger lead to a relatively good performance and that generic taggers do not perform particularly well on this type of data.

1. Introduction

Named entity tagging refers to the task of identifying named entities (such as person names) in a text and assigning them to the appropriate category, e.g., PERSON, ORGANISATION or LOCATION. It is an important subtask for information extraction and retrieval. Named entity tagging is a well studied area, with many implemented systems obtaining performance levels of 80% or more average F-Score (e.g., Florian et al. (2003)). However, most previous research in this area has focused on texts from the news domain is frequently signalled by abbreviations such as “Ldn. or Corp. (e.g., Intel Corp.), whereas organisations in the cultural heritage domain are more likely to be signalled by words such as Museum or Trust (e.g., Perth and Kinross Heritage Trust). Second, language use in databases differs from language use in “normal”, unstructured text; for example, text fields in databases often contain incomplete sentences, as can be seen in example (1) above. The degree and type of incompleteness of sentences in cells of such databases is often triggered by the type of column the cell is in; for example, a column header location of archaeological site may trigger locative phrases in cells of that column (100 miles north of Mexico City).

While porting a generic tagger may prove difficult, it might alternatively be possible to exploit the semi-structured nature of a database to bootstrap a database-specific entity tagger. Usually, the database structure provides implicit information about at least some entities. For example, the St. Andrews Photographic Collection database has a location field, which should contain entities of type LOCATION. Similarly the originator (i.e., photographer) field should contain entities of type PERSON. This can be exploited to automatically create gazetteer lists, which can then form the basis for a simple look-up tagger. Alternatively, the gazetteers can be used to automatically extract examples to train a database-specific tagger. Similar bootstrapping approaches to named entity recognition have been proposed before, though to our knowledge not for textual databases. This paper investigates how successful such an approach could be, and how the performance of such a bootstrapped tagger compares to that of a generic tagger.

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1 http://special.st-andrews.ac.uk/saspecial/
2 http://www.rcahms.gov.uk/index.html
3 http://www.nederlandsesoorten.nl
4 http://www.amazon.com
5 http://www.imdb.com/
2. Related Work

Over the past few years there has been a lot of research into named entity recognition strategies that do not require a large set of manually annotated training examples. A number of approaches exploit the redundancy between word internal and contextual cues (Collins and Singer, 1999; Cucerzan and Yarowsky, 1999). An example of a word internal cue is the fact that a capitalised word starting with the letters Mc is likely to belong to the PERSON class, as in McLeod. An example of a contextual cue is that a word which is followed by Ltd. is likely to be of type ORGANISATION. These two types of cues can be combined in a co-training loop (Blum and Mitchell, 1998). The basic algorithm starts with a small seed list, which is used to label examples in an unannotated corpus. These then form the basis for extracting contextual classification rules which are again applied to the corpus to label additional examples from which word internal rules can be generated, and so on. Phillips and Riloff (2002) also proposed a co-training approach but instead of relying on word internal and contextual cues they exploit the fact that common and proper nouns of the same semantic class tend to co-occur in certain syntactic constructions, such as appositives. For example, if the expression John Seng, the financial analyst is encountered and it is known that John Seng belongs to the PERSON class then it can be inferred that financial analyst also belongs to that class. This in turn allows one to infer that Peter Smith in Peter Smith, the financial analyst is also of type PERSON. Lin et al. (2003) present a bootstrapping approach in which multiple semantic classes are learnt simultaneously on the basis of positive and negative examples. Finally, Buchholz and van den Bosch (2000) collect sizable seed lists from the internet and use these to label training examples in a corpus, which are then used to train a named entity tagger, which can in turn be applied to unlabelled data to gather more names to add to the seed lists. Our approach is similar. However, instead of generating seed lists from the web, we exploit the database structure to create gazetteer lists.

3. Data

We tested our bootstrapping approach on a zoological database containing information about reptile and amphibian specimens, collected by researchers at the Dutch Natural History Museum Naturalis in Leiden. Each database record encodes information about one or more specimens, describing the circumstances of its collection, its position in the zoological taxonomy and so on. The database currently contains about 16,870 records and 35 columns. Some fields (like special remarks) contain more or less free text; others contain entities of a given type (e.g., place contains an expression of type LOCATION).

| Field      | Example                        | Type |
|------------|--------------------------------|------|
| place      | Bigisanti beach                | LOC  |
| province/state land | Marowijne | LOC  |
| land       | Indonesia                      | LOC  |
| author     | Daudin, 1802                   | PER  |
| collector  | Hoogmoed, M.S.                 | PER  |
| donator    | P.J.M. Maas                    | PER  |
| determinant | M.S. Hoogmoed                | PER  |
| recorder   | Grouw, H.J. van                | PER  |
| sub-species | marmoratus                   | TAX  |
| species    | pseudolemniscatus             | TAX  |
| genus      | Anolis                        | TAX  |
| family     | Polychrotidae                  | TAX  |
| order      | Sauria                        | TAX  |
| class      | Reptilia                      | TAX  |

Table 1: Fields from which gazetteers were extracted.

field. Direct extraction from these fields leads to some noise; for example, person fields often contain more than one entity or additional, non-entity material. For instance the author field, which encodes the author of the publication which forms the basis for a species classification, may contain the string Cole & Dessauer, 1993, where 1993 refers to the year in which the publication appeared. We implemented a few simple rules to split multiple expressions and remove additional material. We also used a small list of stop words to identify and remove expressions that are not of the required type. For example, the donator field sometimes contains entities that are organisations (e.g., Museum of Vertebrate Zoology); we identified these by looking for words like museum or collection. Finally, we generalised person names, e.g., if M.S. Hoogmoed was found, we also added Hoogmoed, M.S. and Hoogmoed to the list. Overall we extracted 1,009 expressions of type PER, 3,568 expressions of type LOC and 2,167 expressions of type TAX.

While the gazetteers can be used to identify entities directly via look-up, they can also be used to automatically extract and label training examples (i.e., named entities in context) for a named entity tagger (see Section 2.). Once such a tagger has been trained, it should be able to exploit contextual and word internal cues to identify named entities even when they are not in the original gazetteer lists.

We used one of the free text fields (special remarks) to obtain training and test data for the experiments. When we carried out the experiments, the special remarks field contained around 2200 filled cells. We randomly selected 10% of these for testing and the remaining 90% for training. The text in the test and training sets was then tokenised and the test set was manually annotated with named entity information. In the training set, all expressions for which an exact match was found in one of the gazetteer lists were automatically labelled with the corresponding tag; all other tokens were labelled as OTHER. Table 2 shows the number of tokens in the data sets and the number of tokens for each entity type and for non-entities (OTHER).

We used a rule-based tokeniser for Dutch developed by Sabine Buchholz.
based classifier (TiMBL, (Daelemans et al., 2004)) to identify named entities in free text fields. We employed 65 features, encoding the following information for the target token, the two tokens to the left and the two tokens to the right:

- the token (t) itself
- whether t is capitalised
- whether t contains one or more digits
- whether t contains one or more letters
- the length of t in characters
- whether t contains punctuation
- whether t contains a hyphen
- whether t is utterance/sentence-initial
- whether t is utterance/sentence-final
- the first 4 letters of t
- the last 4 letters of t
- whether t looks like an initial (e.g. E., EM etc.)
- whether t occurred in one of the gazetteers

TiMBL’s parameters (similarity metric, number of nearest neighbours etc.) were set by running a heuristic search algorithm on the training set (wrapped progressive sampling, see van den Bosch (2004)).

### 5. Comparing Three Tagging Strategies

We tested the database-trained tagger on the test set. For comparison, we also applied a look-up tagger, which used our automatically created gazetteers, and a generic named entity tagger for Dutch (Bogers, 2004). The generic tagger was trained and tested on the CoNLL 2002 shared task data (Tjong Kim Sang, 2002). It makes use of a variety of features, such as orthographic information, morphological information, and part-of-speech tags. The tagger distinguishes five classes (PERSON, LOCATION, ORGANISATION, MISCELLANEOUS NAMES, and OTHER). It is reported to perform at around 70% average F-score.

We evaluated all three taggers on a token-by-token basis, calculating precision (P), recall (R) and F-score (F). \(^7\) As the generic tagger does not have the entity category TAXONOMIC, we only evaluated this tagger on PERSON and LOCATION. Table 3 shows the results.

The look-up tagger performs surprisingly well, with an average (macro) F-score of 75.80%. This is in line with previous research which found that good gazetteers combined with a look-up strategy can be remarkably successful (Maynard et al., 2004; Mikheev et al., 1999; Palmer and Day, 1997). The relatively high recall values for the entity classes (in particular for PER) suggest that there is a lot of overlap between entities mentioned in the entity specific database fields and those in the free text fields. The precision is also very high, as one would expect for a look-up strategy. There are two reasons why precision is not perfect. First, some words are ambiguous between two entity classes. For example, Virginia is not only a person name but also a location and part of a taxonomic name (Virginia striatula). Similarly, Iguana usually falls in the category TAX, but in the expression Reptilien Zoo Iguana it should be tagged as OTHER. As the look-up tagger does not use context, it cannot disambiguate between these cases. Another reason for the imperfect precision is that our automatically built gazetteers are not entirely noise-free. For example, the gazetteer for LOC contains the word vindplaats (place of collection), due to the fact that one of the location columns contained the expression vindplaats: Garvoet, Java and this was not filtered out during the gazetteer construction.

The database-trained classifier performs worse than the look-up tagger. It achieves an average (macro) F-score of 68.65%; for all three entity classes both recall and precision are lower than for the look-up tagger. This can be due to several factors. First, it is possible that our training set was simply too small, especially with respect to the three entity classes (with 555 tokens of type PER, 265 of type LOC and 253 of type TAX, see Table 2). It is also possible that differences between the test and training data have a negative effect. For instance, person names in the entity specific fields typically do not contain initials, hence initials are not learnt as being part of a name and are thus frequently misclassified as OTHER in the test set. We experimented with various strategies to improve the results obtained by the database trained tagger (e.g., classifier stacking, combining gazetteer look-up with our classifier etc.), but we were not able to obtain results that are significantly better than those obtained by the look-up tagger.

Finally, for the generic tagger, the results are quite low (around 33% average F-score) and in fact much lower than the results reported for this tagger when testing on newspaper texts (around 70% average F-score). This provides evidence for our hypothesis that a generic named entity tagger is not suited for this type of data. This seems to apply even to non-domain-specific categories, such as PERSON and LOCATION; probably due to domain-specific differences between the training set for this tagger, which came from a news domain, and the test set, which came from a natural history domain, with its fragmented full-text cell content. It is possible that these differences could be partially overcome by using a named entity tagger that was trained on spoken language, as spoken language may be more similar to the language used in textual databases with respect to the degree of fragmentation of sentences.

### 6. Conclusion

We investigated whether it is possible to bootstrap a named entity tagger for textual databases by exploiting the fact that such databases typically contain several entity-specific fields. These fields can be used to automatically extract gazetteer lists, which can then be used by a look-up tag-
Table 3: Results for the three taggers.

|        | Look-up | Database Trained | Generic |
|--------|---------|------------------|---------|
|        | P %    | R %    | F %    | P %    | R %    | F %    | P %    | R %    | F %    |
| PER    | 84.42  | 72.22  | 77.84  | 79.01  | 71.11  | 74.85  | 34.12  | 32.52  | 33.14  |
| LOC    | 65.51  | 45.23  | 53.52  | 56.00  | 33.33  | 41.79  | 75.00  | 21.43  | 33.33  |
| TAX    | 97.56  | 58.82  | 73.39  | 86.11  | 45.59  | 59.62  | —      | —      | —      |
| OTHER  | 97.47  | 99.46  | 98.45  | 97.28  | 99.46  | 98.35  | —      | —      | —      |

The research reported in this paper was funded by NWO (Netherlands Organisation for Scientific Research) and carried out at the Naturalis Research Labs in Leiden. We would like to thank the staff at Naturalis and the three anonymous reviewers for their comments and suggestions.

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