Adaptive Sentence Boundary Disambiguation

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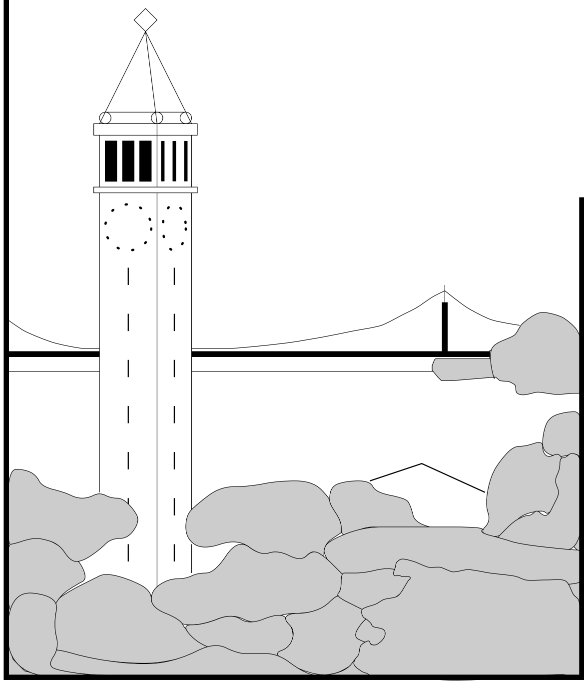

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Abstract

Labeling of sentence boundaries is a necessary prerequisite for many natural language processing tasks, including part-of-speech tagging and sentence alignment. End-of-sentence punctuation marks are ambiguous; to disambiguate them most systems use brittle, special-purpose regular expression grammars and exception rules. As an alternative, we have developed an efficient, trainable algorithm that uses a lexicon with part-of-speech probabilities and a feed-forward neural network. After training for less than one minute, the method correctly labels over 98.5% of sentence boundaries in a corpus of over 27,000 sentence-boundary marks. We show the method to be efficient and easily adaptable to different text genres, including single-case texts.

1 Introduction

Labeling of sentence boundaries is a necessary prerequisite for many natural language processing (NLP) tasks, including part-of-speech tagging (Church, 1988),(Cutting et al., 1991), and sentence alignment (Gale and Church, 1993), (Kay and Röscheinsen, 1993). End-of-sentence punctuation marks are ambiguous; for example, a period can denote an abbreviation, or the end of a sentence, as shown in the examples below:

(1) *The group included Dr. J.M. Freeman and T. Boone Pickens Jr.*

(2) *"This issue crosses party lines and crosses philosophical lines!" said Rep. John Rowland (R., Conn.).*

Riley (Riley, 1989) determined that in the Tagged Brown corpus (Francis and Kucera, 1982) about 90% of periods occur at the end of sentences, 10% at the end of abbreviations, and about 0.5% as both abbreviations and sentence delimiters.

Most robust NLP systems (e.g., (Cutting et al., 1991)) tokenize the text stream and apply a regular expression grammar with some amount of look-ahead, an abbreviation list, and perhaps a list of exception rules. These approaches usually are hand-tailored to the text at hand and rely on brittle parameters such as capitalization and the number of spaces following a sentence delimiter. Typically these approaches use only the tokens immediately preceding and following the punctuation mark to be disambiguated. However, more context can be necessary, such as when an abbreviation appears at the end of a sentence, as seen in (3a-b),

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(3a) *It was due Friday by 5 p.m. Saturday would be too late.*

(3b) *She has an appointment at 5 p.m. Saturday to get her car fixed.*

or when punctuation occurs in a subsentence within quotation marks or parentheses as seen in Example 2.

Some systems have achieved accurate boundary determination via very large manual effort. For example, at Mead Data Central, Mark Wasson and colleagues, over a period of 9 staff months, developed a system that recognizes special tokens (e.g., non-dictionary terms such as proper names, legal statute citations, etc.) as well as sentence boundaries. From this, Wasson built a stand-alone boundary recognizer in the form of a grammar converted into finite automata with 1419 states and 18002 transitions (excluding the lexicon). The resulting system, when tested on 20 megabytes of news and case law text achieved an accuracy of 99.7% at speeds of 80,000 characters per CPU second on a mainframe computer. When tested against upper-case legal text the algorithm still performed very well, achieving accuracies of 99.71% and 98.24% on test data of 5305 and 9396 periods, respectively. It is not likely, however, that the results would be this strong on lower-case data.[1]

Humphrey and Zhou (Humphrey and Zhou, 1989) report using a feed-forward neural network to disambiguate periods, although they use a regular grammar to tokenize the text before training the neural nets, and achieve an accuracy averaging 93%.[2].

Riley (Riley, 1989) describes an approach that uses regression trees (Breiman et al., 1984) to classify sentence boundaries according to the following features:

Probability[word preceding "." occurs at end of sentence]
Probability[word following "." occurs at beginning of sentence]
Length of word preceeding "."
Length of word after "."
Case of word preceeding ".": Upper, Lower, Cap, Numbers
Case of word following ".": Upper, Lower Cap, Numbers
Punctuation after "." (if any)
Abbreviation class of words with "."

The method uses information about one word of context on either side of the punctuation mark and thus must record for every word in the lexicon the probability that it occurs next to a sentence boundary. Probabilities were compiled from 25 million words of pre-labeled training data from a corpus of AP newswire. The results were tested on the Brown corpus achieving an accuracy of 99.8%.[3]

Müller (Müller et al., 1980) provides an exhaustive analysis of sentence boundary disambiguation as it relates to lexical endings and the identification of words surrounding a punctuation mark, focusing on text written in English. This approach makes multiple passes through the data and uses large word lists to determine the positions of full stops. Accuracy rates of 95-98% are reported for this method tested on over 75,000 scientific abstracts. (In contrast to Riley's Brown corpus statistics, Müller reports sentence-ending to abbreviation ratios ranging from 92.8%/7.2% to 54.7%/45.3%. This implies a need for an approach that can adapt flexibly to different text collections.)

Each of these approaches has disadvantages to overcome. We propose that a sentence-boundary disambiguation algorithm have the following characteristics:

[1]All information about Mead's system is courtesy of a personal communication with Mark Wasson.

[2]Accuracy results were obtained courtesy of a personal communication with Joe Zhou.

[3]Time for training was not reported, nor was the amount of the Brown corpus against which testing was performed; we assume the entire Brown corpus was used.

- The approach should be robust, and should not require a hand-built grammar or specialized rules that depend on capitalization, multiple spaces between sentences, etc. Thus, the approach should adapt easily to new text genres and new languages.
- The approach should train quickly on a small training set and should not require excessive extra storage overhead.
- The approach's results should be very accurate and very efficient so that it does not noticeably slow down the NLP system's preprocessing stage.
- The approach should be able to specify "no opinion" on cases that are too difficult to disambiguate, rather than making underinformed guesses.

In the following sections we present an approach that meets each of these criteria, performing as well as or better than solutions that require manually designed rules, and behaving more robustly. Section 2 describes the algorithm, Section 3 describes some experiments evaluating the algorithm, and Section 4 summarizes the paper and describes future directions.

2 Our Solution

We have developed an efficient and accurate automatic sentence boundary labeling algorithm which overcomes the limitations of previous solutions. The method is easily trainable and adapts to new text types without requiring rewriting of recognition rules.

Our method is simple, yet effective: the part-of-speech probabilities of the tokens surrounding a punctuation mark are input to a feed-forward neural network, and the network's output activation value indicates the role of the punctuation mark.

The straightforward approach to using contextual information is to record for each word the likelihood that it appears before or after a sentence boundary. However, it is expensive to obtain probabilities for likelihood of occurrence of all individual tokens in the positions surrounding the punctuation mark, and most likely such information would not be useful to any subsequent processing steps in an NLP system. Instead, we use probabilities for the part-of-speech categories of the surrounding tokens, thus making training faster and storage costs negligible for a system that must in any case record these probabilities for use in its part-of-speech tagger.

A processing cycle can arise here: because most part-of-speech taggers require pre-determined sentence boundaries, sentence labeling must be done before tagging. But if sentence labeling is done before tagging, where do the part-of-speech assignments used by the boundary-determiner come from? Instead of assigning a single part-of-speech to each word, our algorithm uses *the prior probabilities* of all parts-of-speech for that word. Recall that Riley's method (Riley, 1989) requires special-case probabilities for every lexical item, since it records the number of times every token has been seen before and after a period. In contrast, we make use of the unchanging prior probabilities for each word already stored in the system's lexicon.

The rest of this section describes the algorithm in more detail.

2.1 Assignment of Descriptors

The first stage of the process is lexical analysis, which breaks the input text (a stream of characters) into tokens. Our implementation uses a slightly-modified version of the tokenizer from the PARTS part-of-speech tagger (Church, 1988) for this task. A token can be a sequence of alphabetic characters, a sequence of digits (numbers containing periods acting as decimal points are considered a single token), or a single non-alphanumeric character. A

1. noun
2. verb
3. article
4. modifier
5. conjunction
6. pronoun
7. preposition
8. proper noun
9. number
10. comma or semicolon
11. left parentheses
12. right parentheses
13. non-punctuation character
14. possessive
15. colon or dash
16. abbreviation
17. sentence-ending punctuation
18. others

Figure 1: Elements of the Descriptor Array assigned to each incoming token.

lookup module then uses a lexicon with part-of-speech tags for each token, including the frequency with which that word occurs as each possible part-of-speech. The lexicon and the frequency counts were also taken from the PARTS tagger, which derived the counts from the Brown corpus (Francis and Kucera, 1982). For the word *adult*, for example, the lookup module would return the tags "JJ/2 NN/24," signifying that the word occurred 26 times in the Brown corpus – twice as an adjective and 24 times as a singular noun.

The lexicon contains 77 part-of-speech tags, which we map into 18 more general categories (see Figure 1). For example, the tags for present tense verb, past participle, and modal verb all map into the more general "verb" category. For a given word and category, the frequency of the category is the sum of the frequencies of all the tags that are mapped to the category for that word. The 18 category frequencies for the word are then converted to probabilities by dividing the frequencies for each category by the total number of occurrences of the word.

For each token that appears in the input stream, a descriptor array is created consisting of the 18 probabilities as well as two additional flags that indicate if the word begins with a capital letter and if it follows a punctuation mark.

2.2 The Role of the Neural Network

We accomplish the disambiguation of periods (as well as exclamation points and question marks) using a feed-forward neural network trained with the back propagation algorithm (Hertz et al., 1991). The network accepts as input $k*20$ input units, where k is the number of words of context surrounding an instance of an end-of-sentence punctuation mark (referred to in this paper as "k-context"), and 20 is the number of elements in the descriptor array described in the previous subsection. The input layer is fully connected to a hidden layer consisting of j hidden units with a sigmoidal squashing activation function. The hidden units in turn feed into one output unit which indicates the results of the function. [4]

[4] The context of a punctuation mark can be thought of as the sequence of tokens preceding and following it. Thus this network can be thought of roughly as a Time-Delay Neural Network (TDNN) (Hertz et al., 1991), since it accepts a sequence of inputs and is sensitive to positional information within the sequence. However, since the input information is not really shifted with each time step, but rather only presented to the neural net when a punctuation mark is in the center of the input stream, this is not technically a TDNN.

The output of the network, a single value between 0 and 1, represents the strength of the evidence that a punctuation mark occurring in its context is indeed the end of the sentence. We define two adjustable sensitivity thresholds t_0 and t_1, which are used to classify the results of the disambiguation. If the output is less than t_0, the punctuation mark is not a sentence boundary; if the output is greater than or equal to t_1, it is a sentence boundary. Outputs which fall between the thresholds cannot be disambiguated by the network and are marked accordingly so they can be treated specially in later processing. When $t_0 = t_1$, every punctuation mark is labeled as either a boundary or a non-boundary.

To disambiguate a punctuation mark in a k-context, a window of $k + 1$ tokens and their descriptor arrays is maintained as the input text is read. The first $k/2$ and final $k/2$ tokens of this sequence represent the context in which the middle token appears. If the middle token is a potential end-of-sentence punctuation mark, the descriptor arrays for the context tokens are input to the network and the output result indicates the appropriate label, subject to the thresholds t_0 and t_1.

Section 3 describes experiments in which the size of k, the number of hidden units, and the thresholds are varied.

2.3 Heuristics

A connectionist network can discover patterns in the input data without using explicit rules, but the input must be structured to allow the net to recognize these patterns. Important factors in the effectiveness of these arrays include the mapping of part-of-speech tags into categories, and assignment of parts-of-speech to words not explicitly contained in the lexicon.

As previously described, we map the part-of-speech tags in the lexicon to more general categories. This mapping is, to an extent, dependent on the range of tags and on the language being analyzed. In our experiments, when all verb forms in English are placed in a single category, the results are strong (although we did not try alternative mappings). We speculate, however, that for languages like German, the verb forms will need to be separated from each other, as certain forms occur much more frequently at the end of a sentence than others do. The same may be true for other parts-of-speech in certain languages.

Another important consideration is classification of words not present in the lexicon, since most texts contain infrequent words. Particularly important is the ability to recognize tokens that are likely to be abbreviations or proper nouns. We attempt to identify initials by assigning an "abbreviation" tag to all sequences of letter containing internal periods and no spaces. This finds abbreviations like "J.R." and "Ph.D." Note that the final period is a punctuation mark which needs to be disambiguated, and is therefore not considered part of the word.

A capitalized word is not necessarily a proper noun, even when it appears somewhere other than in a sentence's initial position (e.g., the word "American" is often used as an adjective). We require a way to assign probabilities to capitalized words that appear in the lexicon but are not registered as proper nouns. We use a simple heuristic: we split the word's probabilities, assigning a 0.5 probability that the word is a proper noun, and dividing the remaining 0.5 according to the proportions of the probabilities of the parts of speech indicated in the lexicon.

Capitalized words that do not appear in the lexicon at all are more likely to be proper nouns; therefore, they are assigned a proper noun probability of 0.9, with the remaining 0.1 probability distributed equally among all the other parts-of-speech. These simple assignment rules are effective for English, but would need to be slightly modified for other languages with different capitalization rules (e.g., in German all nouns are capitalized.)

3 Experiments and Results

We tested the boundary labeler on a large body of text containing 27,294 potential sentence-ending punctuation marks taken from the Wall Street Journal portion of the ACL/DCI collection (Church and Liberman, 1991). No preprocessing was performed on the test text, aside from removing unnecessary headers and correcting existing errors. (The sentence boundaries in the WSJ text had been previously labeled using a method similar to that used in PARTS and is described in more detail in (Liberman and Church, 1992); we found and corrected several hundred errors.) We trained the weights in the neural network with a back-propagation algorithm on a training set of 573 items from the same corpus. To increase generalization of training, a separate cross-validation set (containing 258 items also from the same corpus) was also fed through the network, but the weights were not trained on this set. When the cumulative error of the items in the cross-validation set reached a minimum, training was stopped. The entire training procedure required less than one minute on a Hewlett Packard 9000/750 Workstation. This should be contrasted with Riley's algorithm which required 25 million words of training data in order to compile probabilities.

If we use Riley's statistics presented in Section 1, we can determine a lower bound for a sentence boundary disambiguation algorithm: an algorithm that always labels a period as a sentence boundary would be correct 90% of the time; therefore, any method must perform better than 90%. Performance was very strong: with both sensitivity thresholds set to 0.5, the network method was successful in disambiguating 98.5% of the punctuation marks, mislabeling only 409 of 27,294. These errors fall into two major categories: 1)"false positive," a punctuation mark the method erroneously labeled as a sentence boundary, and 2) "false negative," an actual sentence boundary which the method did not label as such. See Table 1.

224 (54.8%) false positives
185 (45.2%) false negatives
409 total errors out of 27,294 items

Table 1: Results of testing on 27,294 mixed-case items; $t_0 = t_1 = 0.5$, 6-context, 2 hidden units.

The 409 errors from this testing run can be decomposed into the following groups:

- 37.6% false positive at an abbreviation within a title or name, usually because the word following the period exists in the lexicon with other parts-of-speech (*Mr. Gray, Col. North, Mr. Major, Dr. Carpenter, Mr. Sharp*). Also included in this group are items such as *U.S. Supreme Court* or *U.S. Army*, which are sometimes mislabeled because *U.S.* occurs very frequently at the end of a sentence as well.
- 22.5% false negative due to an abbreviation at the end of a sentence, most frequently *Inc., Co., Corp.*, or *U.S.*, which all occur within sentences as well.
- 11.0% false positive or negative due to a sequence of characters including a period and quotation marks, as this sequence can occur both within and at the end of sentences.
- 9.2% false negative resulting from an abbreviation followed by quotation marks; related to the previous two types, this case is twice as difficult to disambiguate due to the combination of both.
- 9.8% false positive or false negative resulting from presence of ellipsis (...), which can occur at the end or within a sentence.
- 9.9% miscellaneous errors, including extraneous characters (dashes, asterisks, etc.), ungrammatical sentences, misspellings, and parenthetical sentences.

The results presented above (409 errors) are obtained when both t_0 and t_1 are set at 0.5. Adjusting the sensitivity thresholds decreases the number of punctuation marks which are mislabeled by the method. For example, when the upper threshold are set at 0.8 and the lower threshold at 0.2, the network places 164 items between the two. This indicates that the algorithm does not have enough evidence to classify the items, and thus allows it to avoid mislabeling them.

We experimented with different context sizes and number of hidden units in the neural network, and we obtained the results shown in Tables 2 and 3. All results were obtained using the same training set of 573 items, cross-validation set of 258 items, and mixed-case test set of 27,294 items. (We also tested the network with larger numbers of hidden units and larger training sets, but results of these tests all had error rates over 10% and are thus not reported.) The "Training Error" is one-half the sum of all the errors for all 573 items in the training set, where the "error" is the difference between the desired output and the actual output of the neural net. The "Cross Error" is the equivalent value for the cross-validation set. These two error figures give an indication of how well the network learned the training data before stopping.

Context Size	Training Epochs	Training Error	Cross Error	Testing Errors	Testing Error (%)
4-context	1731	1.52	2.36	1424	5.22%
6-context	218	0.75	2.01	409	1.50%
8-context	831	0.043	1.88	877	3.21%

Table 2: Results of comparing context sizes.

# Hidden Units	Training Epochs	Training Error	Cross Error	Testing Errors	Testing Error (%)
1	623	1.05	1.61	721	2.64%
2	216	1.08	2.18	409	1.50%
3	239	0.39	2.27	435	1.59%
4	350	0.27	1.42	1343	4.92%

Table 3: Results of comparing hidden layer sizes. (6-context)

From these data we concluded that a context of six surrounding tokens and a hidden layer with two units worked best for our test set.

After converting the training, cross-validation and test texts to a lower-case-only format and retraining, the network was able to successfully disambiguate 96.2% of the boundaries in a lower-case-only test text. Repeating the procedure with an upper-case-only format produced a 97.4% success rate. Unlike most existing methods which rely heavily on capitalization information, the network method can accurately disambiguate single-case texts.

4 Discussion and Future Work

We have presented an automatic sentence boundary labeler which uses probabilistic part-of-speech information and a simple neural network to correctly disambiguate over 98.5% of sentence-boundary punctuation marks. A novel aspect of the approach is its use of part-of-speech probabilities, rather than word tokens, to represent the context surrounding the punctuation mark to be disambiguated. This leads to savings in parameter estimation and thus training time. The stochastic nature of the input, combined with the inherent robustness of the connectionist network, produces robust results. The network is rapidly trainable and thus should be easily adaptable to new text genres, and is very efficient when used in its labeling capacity.

Although our results were obtained using an English lexicon and text, we designed the boundary labeler to be equally applicable to other languages, assuming the accessibility of lexical part-of-speech frequency data (which can be obtained by running a part-of-speech tagger over a large corpus of text, if it is not available in the tagger itself) and an abbreviation list. The input to the neural network is a language-independent set of descriptor arrays, so training and labeling would not require recoding for a new language. The heuristics described in Section 2 may need to be adjusted for other languages in order to maximize the efficacy of these descriptor arrays. We plan to test the approach on French and perhaps German. We also plan to apply the approach to texts with unusual or very loosely constrained markup formats, and perhaps even to other markup recognition problems. We plan also to compare the use of a neural net with more conventional computational linguistics tools such as ngrams and Hidden Markov Models.

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