Simple Features for Statistical Word Sense Disambiguation

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Abstract
In this paper, we describe our experiments on statistical word sense disambiguation (WSD) using two systems based on different approaches: Naive Bayes on word tokens and Maximum Entropy on local syntactic and semantic features. In the first approach, we consider a context window and a sub-window within it around the word to disambiguate. Within the outside window, only content words are considered, but within the sub-window, all words are taken into account. Both window sizes are tuned by the system for each word to disambiguate and accuracies of 75% and 67% were respectively obtained for coarse and fine-grained evaluations. In the second system, sense resolution is done using an approximate syntactic structure as well as semantics of neighboring nouns as features to a Maximum Entropy learner. Accuracies of 70% and 63% were obtained for coarse and fine-grained evaluations.

1 Introduction
In this paper, we present the two systems we built for our first participation in the English lexical sample task at Senseval-3. In the first system, a Naive Bayes learner based on context words as features is implemented. In the second system, an approximate syntactic structure, in addition to semantics of the nouns around the ambiguous word are selected as features to learn with a Maximum Entropy learner.

In Section 2, a brief overview of related work on WSD is presented. Sections 3 and 4 provide specifications of our two systems. Section 5 discusses the results obtained and remarks on them, and finally in Section 6, conclusion and our future work direction are given.

2 Related Work
In 1950, Kaplan carried out one of the earliest WSD experiments and showed that the accuracy of sense resolution does not improve when more than four words around the target are considered (Ide and Véronis, 1998). While researchers such as Masterman (1961), Gougenheim and Michea (1961), agree with this observation (Ide and Véronis, 1998), our results demonstrate that this does not generally apply to all words. A large context window provides domain information which increases the accuracy for some target words such as bank.n, but not others like different.a or use.v (see Section 3). This confirms Mihalcea’s observations (Mihalcea, 2002). In our system we allow a larger context window size and for most of the words such context window is selected by the system.

Another trend consists in defining and using semantic preferences for the target word. For example, the verb drink prefers an animate subject in its imbibe sense. Boguraev shows that this does not work for polysemous verbs because of metaphoric expressions (Ide and Véronis, 1998).

Furthermore, the grammatical structures the target word takes part in can be used as a distinguishing tool: “the word ‘keep’, can be disambiguated by determining whether its object is gerund (He kept eating), adjectival phrase (He kept calm), or noun phrase (He kept a record)” (Reifler, 1955). In our second system we approximate the syntactic structures of a word, in its different senses.

Mooney (Mooney, 1996) has discussed the effect of bias on inductive learning methods. In this work we also show sensitivity of Naive Bayes to the distribution of samples.

3 Naive Bayes for Learning Context Words
In our approach, a large window and a smaller sub-window are centered around the target word. We account for all words within the sub-window but use a POS filter as well as a short stop-word list to filter out non-content words...
The best accuracy is achieved with a window and sub-window size of around 450 and 50 characters respectively, while for example 50 and 25 provide very low accuracy.

from the context. The filter retains only open class words, i.e. nouns, adjectives, adverbs, and verbs, and rejects words tagged otherwise.

3.1 Changing the context window size

Figure 1 shows the effect of selecting different window and sub-window sizes for the word bank\textit{n}. It is clear that precision is very sensitive to the selected window size. Other words also have such variations in their precision results.

The system decides on the best window sizes for every word by examining possible window size values ranging from 25 to 750 characters\footnote{For technical reasons, character is used instead of word as the unit, making sure no word is cut at the extremities.}. Table 1 shows the optimal window sizes selected for a number of words from different word classes. The baseline is considered individually for every word as the ratio of the most common sense in the training samples. We used the Senseval-3 training set for the English lexical sample task for training. It includes a total of 7860 tagged samples for 57 ambiguous words. 15\% of this data was used for validation, while the rest was used for training.

3.2 Approximate Smoothing

During the testing phase, given the context of the target word, the score of every sense is computed using the Naive Bayes formula:

$$Score_{sense_i} = \log p(sense_i) + \sum_{k} \log p(word_k)$$

where, \textit{word}_k is every word inside the context window (recall that these are all the words in the sub-window, and filtered words in the large window).

Various smoothing algorithms could be used to reduce the probability of seen words and distributing them among unseen words. However, tuning various smoothing parameters is delicate as it involves keeping an appropriate amount of held-out data. Instead, we implemented an approximate smoothing method, which seems to perform better compared to Ng’s (Ng, 1997) approximate smoothing. In our simple approximate smoothing the probability of seen words is not discounted to compensate for those of unseen words\footnote{This results in a total probability mass larger than 1; but still allows us to rank the probability of the senses.}. Finding a proper value to assign to unseen words was done experimentally; for a relatively large training data set, \(p(\text{an unseen word}) = 10^{-10}\) and for a small set, \(10^{-9}\) resulted in the highest accuracy with our 15\% validation set\footnote{The logarithm was taken in base 10.}. The intuition is that, with a small training set, more unseen words are likely to be seen during the testing phase, and in order to prevent the accumulating score penalty value from becoming relatively high, a lower probability value is selected. Additionally, the selection should not result in large differences in the computed scores of different senses of the target word.

A simple function assigns \(10^{-10}\) in any of the following conditions: the total number of words seen is larger than 4300, the number of training instances is greater than 230, or the context window size is larger than 400 characters. The function returns \(10^{-9}\) otherwise.

4 Maximum Entropy learning of syntax and semantics

Syntactic structures as well as semantics of the words around the ambiguous word are strong clues for sense resolution in many words. However, deriving and using exact syntactic information introduces its own difficulties. So, we tried to use approximate syntactic structures by learning the following features in a context window bounded by the last punctuation before and the first punctuation after the ambiguous word:

1. \textit{Article Bef}: If there is any article before, the string token is considered as the value of this feature.

2. \textit{POS, POS Bef, POS Aft}: The part of speech of the target, the part of speech of the word before (after) if any.
3. Prep Bef, Prep Aft: The last preposition before, and the first preposition after the target, if any.

4. Sem Bef, Sem Aft: The general semantic category of the noun before (after) the target. The category, which can be ‘animate’, ‘inanimate’, or ‘abstract’, is computed by traversing hypernym synsets of WordNet for all the senses of that noun. The first semantic category observed is returned, or ‘inanimate’ is returned as the default value.

The first three items are taken from Mihalcea’s work (Mihalcea, 2002) which are useful features for most of the words. The range of all these features are closed sets; so Maximum Entropy is not biased by the distribution of the senses in the training samples and the number of training samples available for a word. Indeed, a large window size is selected when the number of samples is large, and the samples are not evenly distributed among senses. Basically because the words in Senseval are not mostly topical words, Naive Bayes is working strongly with the commonest effect. On the other hand, when a small window size is selected, the commonest effect mostly vanishes and instead, collocations are relied upon.

5.2 Distribution of samples
A Naive Bayes method is quite sensitive to the proportion of training and test samples: if the commonest class presented as test is different from the commonest class in training for example, this method performs poorly. This is a serious problem of Naive Bayes towards real world WSD. For testing this claim, we made the following hypothesis: When the mean of absolute difference of the test samples and training samples among classes of senses is more than 4%, Naive Bayes method performs at most 20% above baseline. Table 3 shows that this hypothesis is confirmed in 82% of the cases (41 words)

5 Results and Discussion
The Word Sense Disambiguator program has been written as a Processing Resource in the Gate Architecture. It uses the ANNIE Tagger and POS Tagger which are provided as components of Gate.

Table 2 shows the results of both systems for each category of words. It can be seen that approximate syntactic information has performed relatively better with adjectives which are generally harder to disambiguate.

5.1 Window size and the commonest effect
The optimal window size seems to be related to the distribution of the senses in the training samples and the number of training samples available for a word. Indeed, a large window size is selected when the number of samples is large, and the samples are not evenly distributed among senses. Basically because the words in Senseval are not mostly topical words, Naive Bayes is working strongly with the commonest effect. On the other hand, when a small window size is selected, the commonest effect mostly vanishes and instead, collocations are relied upon.

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Table 3: Sensitivity of Naïve Bayes to the distribution of samples (Acc=Accuracy amount higher than baseline; Dist=Mean of distribution change.)

| Dist ≤ 4.0 | 5  | 26 |
| Dist > 4.0 | 15 | 4  |

out of 50 ambiguous words that satisfy the conditions). Furthermore, such words are not necessarily difficult words. Our Maximum Entropy method performed on average 25% above the baseline on 7 of them (ask.v, decide.v, different.a, difficulty.n, sort.n, use.v, wash.v some of which are shown in Table 1).

5.3 Rare samples
Naïve Bayes mostly ignores the senses with a few samples in the training and gets its score on the senses with large number of training instances, while Maximum Entropy exploits features from senses which have a few training samples.

5.4 Using lemmas and synsets
We tried working with word lemmas instead of derivated forms; however, for some words it causes loss in accuracy. For example, for the adjective different.a, with window and sub-window size of 175 and 0, it reduces the accuracy from 60% to 46% with the validation set. However, for the noun sort.n, precision increases from 62% to 72% with a window size of 650 and sub-window size of 50. We believe that some senses come with a specific form of their neighboring tokens and lemmatization removes this distinguishing feature.

We also tried storing synsets of words as features for the Naïve Bayes learner, but obtained no significant change in the results.

6 Conclusion and Future Work
There is no fixed context window size applicable to all ambiguous words in the Naïve Bayes approach: keeping a large context window provides domain information which increases the resolution accuracy for some target words but not others. For non-topical words, large window size is selected only in order to exploit the distribution of samples.

Rough syntactic information performed well in our second system using Maximum Entropy modeling. This suggests that some senses can be strongly identified by syntax, leaving resolution of other senses to other methods. A simple, rough heuristic for recognizing when to rely on syntactic information in our system is when the selected window size by Naïve Bayes is relatively small.

We tried two simple methods for combining the two methods: considering context words as features in Max Entropy learner, and, establishing a separate Naïve Bayes learner for each syntactic/semantic feature and adding their scores to the basic contextual Naïve Bayes. These preliminary experiments did not result in any noticeable improvement.

Finally, using more semantic features from WordNet, such as verb sub-categorization frames (which are not consistently available) may help in distinguishing the senses.

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