Naive Bayes and Exemplar-Based approaches to Word Sense Disambiguation Revisited

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Abstract. This paper describes an experimental comparison between two standard supervised learning methods, namely Naive Bayes and Exemplar–based classification, on the Word Sense Disambiguation (WSD) problem. The aim of the work is twofold. Firstly, it attempts to contribute to clarify some confusing information about the comparison between both methods appearing in the related literature. In doing so, several directions have been explored, including: testing several modifications of the basic learning algorithms and varying the feature space. Secondly, an improvement of both algorithms is proposed, in order to deal with large attribute sets. This modification, which basically consists in using only the positive information appearing in the examples, allows to improve greatly the efficiency of the methods, with no loss in accuracy. The experiments have been performed on the largest sense–tagged corpus available containing the most frequent and ambiguous English words. Results show that the Exemplar–based approach to WSD is generally superior to the Bayesian approach, especially when a specific metric for dealing with symbolic attributes is used.

1 INTRODUCTION

Word Sense Disambiguation (WSD) is the problem of assigning the appropriate meaning (sense) to a given word in a text or discourse. Resolving the ambiguity of words is a central problem for language understanding applications and their associated tasks [1], including, for instance, machine translation, information retrieval and hypertext navigation, parsing, speech synthesis, spelling correction, reference resolution, automatic text summarization, etc.

WSD is one of the most important open problems in the Natural Language Processing (NLP) field. Despite the wide range of approaches investigated and the large effort devoted to tackle this problem, it is a fact that to date no large–scale broad–coverage and highly accurate word sense disambiguation system has been built.

One of the most successful current lines of research is the corpus–based approach in which statistical or Machine Learning (ML) algorithms have been applied to learn statistical models or classifiers from corpora in order to perform WSD. Generally, supervised approaches (those that learn from a previously semantically annotated corpus) have obtained better results than unsupervised methods on small sets of selected highly ambiguous words, or artificial pseudo–words. Many standard ML algorithms for supervised learning have been applied, such as: Bayesian learning [3, 19], Exemplar–based learning [18, 16, 5], Decision Lists [21], Neural Networks [20], etc. Further, Mooney [13] provides a comparative experiment on a very restricted domain between all previously cited methods but also including Decision Trees and Rule Induction algorithms.

Despite the good results obtained on limited domains, supervised methods suffer from the lack of widely available semantically tagged corpora, from which to construct really broad coverage systems. This is known as the “knowledge acquisition bottleneck” [6]. Ng [17] estimates that the manual annotation effort necessary to build a broad coverage semantically annotated corpus would be about 16 man–years. This extremely high overhead for supervision and, additionally, the also serious learning overhead when common ML algorithms scale to real size WSD problems, explain why supervised methods have been seriously questioned.

Due to this fact, recent works have focused on reducing the acquisition cost as well as the need for supervision of corpus–based methods for WSD. Consequently, the following three lines of research are currently being studied: 1) The design of efficient example sampling methods [3, 8]; 2) The use of lexical resources, such as WordNet [13], and WWW search engines to automatically obtain from Internet accurate and arbitrarily large word sense samples [13, 5]; 3) The use of unsupervised EM–like algorithms for estimating the statistical model parameters [19]. It is our belief that this body of work, and in particular the second line, provide enough evidence towards the “opening” of the acquisition bottleneck in the near future. For that reason, it is worth further investigating the application of supervised ML methods to WSD, and thoroughly comparing existing alternatives.

1.1 Comments about Related Work

Unfortunately, there have been very few direct comparisons between alternative methods for WSD. However, it is commonly stated that Naive Bayes, Neural Networks and Exemplar–based learning represent state–of–the–art accuracy on supervised WSD [16, 15, 18, 12]. Regarding the comparison between Naive Bayes and Exemplar–based methods, the works by Mooney [13] and Ng [17] will be the ones basically referred to in this paper.

Mooney’s paper shows that the Bayesian approach is clearly superior to the Exemplar–based approach. Although it is not explicitly said, the overall accuracy of Naive Bayes is about 16 points higher than that of the Example–based algorithm, and the latter is only slightly above the accuracy that a Most–Frequent–Sense classifier would obtain. In the Exemplar–based approach, the algorithm applied for classifying new examples was a standard k–Nearest–Neighbour (k–NN), using the Hamming distance for measuring closeness. Neither example weighting nor attribute weighting are applied, k is set to 3, and the number of attributes used is said to be almost 3,000.

The second paper compares the Naive Bayes approach with Pe-
2.2 Exemplar-Based Approach

In our basic implementation all examples are stored in memory and the classification of a new example is based on a \( k \)-NN algorithm, which uses Hamming distance to measure closeness (in doing so, all examples are examined). If \( k \) is greater than 1, the resulting sense is the majority sense of the \( k \) nearest neighbours. Ties are resolved in favour of the most frequent sense among all those tied. Hereinafter, this algorithm will be referred to as \( \text{EB}_{h,k} \).

In order to test some of the hypotheses about the differences between Naive Bayes and Exemplar–based approaches, some variants of the basic \( k \)-NN algorithm have been implemented:

- **Example weighting.** This variant introduces a simple modification in the voting scheme of the \( k \) nearest neighbours, which makes the contribution of each example proportional to their importance. When classifying a new test example, each example of the set of nearest neighbours votes for its class with a weight proportional to its closeness to the test example. Hereinafter, this variant will be referred to as \( \text{EB}_{h,k,e} \).

- **Attribute weighting.** This variant consists of ranking all attributes by relevance and making them contribute to the distance calculation with a weight proportional to their importance. The attribute weighting has been done using the RLM distance measure \( \text{RLM} \). This measure, belonging to the distance/information–based families of attribute selection functions, has been selected because it showed better performance than seven other alternatives in an experiment of decision tree induction for PoS tagging \( \text{EB}_{h,k,a} \). Hereinafter, this variant will be referred to as \( \text{EB}_{h,k,a} \).

When both modifications are put together, the resulting algorithm will be referred to as \( \text{EB}_{h,k,e,a} \). Finally, we have also investigated the effect of using an alternative metric.

- **Modified Value Difference Metric (MVD),** proposed by Cost and Salzberg \( \text{EB}_{h,k} \), allows making graded guesses of the match between two different symbolic values. Let \( v_1 \) and \( v_2 \) be two values of a given attribute \( a \). The MVD distance between them is defined as:

\[
d(v_1, v_2) = \sum_{i=1}^{m} |P(C_i | v_1) - P(C_i | v_2)| \approx \sum_{i=1}^{m} \left| \frac{N_{v_1,i}}{N_1} - \frac{N_{v_2,i}}{N_2} \right|
\]

where \( m \) is the number of classes, \( N_{v,a,i} \) is the number of training examples with value \( v_a \) of attribute \( a \) that are classified as class \( i \) in the training corpus and \( N_i \) is the number of training examples with value \( v_a \) of attribute \( a \) in any class. Hereinafter, this variant will be referred to as \( \text{EB}_{v,a,k} \). This algorithm has also been used with the example–weighting facility \( \text{EB}_{v,e,a} \).

3 SETTING

In our experiments, both approaches have been evaluated on the DSO corpus, a semantically annotated corpus containing 192,800 occurrences of 121 nouns and 70 verbs\( \text{EB}_{h,k} \), corresponding to the most frequent and ambiguous English words. This corpus was collected by Ng and colleagues \( \text{EB}_{h,k} \) and it is available from the Linguistic Data Consortium (LDC).

\[2\] These examples, consisting of the full sentence in which the ambiguous word appears, are tagged with a set of labels corresponding, with minor changes, to the senses of WordNet 1.5.

\[3\] LDC address: \url{http://www.ldc.upenn.edu/}
For our first experiments, a group of 15 words (10 nouns and 5 verbs) which frequently appear in the WSD literature has been selected. These words are described in the left hand–side of table 1. Let \( \cdots \) be the context of consecutive words around the word \( w \) to be disambiguated. Attributes refer to this context as follows.

- **SETA** contains the seven following attributes: \( w_{-2}, w_{-1}, w_{+1}, w_{+2}, (w_{-2}, w_{-1}), (w_{-1}, w_{+1}), (w_{+1}, w_{+2}) \), where the last three correspond to collocations of two consecutive words. These attributes, which are exactly those used in [16], represent the local context of the ambiguous word and they have been proven to be very informative features for WSD. Note that whenever an attribute refers to a position that falls beyond the boundaries of the sentence for a certain example, a default value \( \cdots \) is assigned.

Let \( p_{2j} \) be the part–of–speech tag of word \( w_{2j} \), and \( c_1, \ldots, c_m \) the unordered set of open class words appearing in the sentence.

- **SETB** enriches the local context: \( w_{-1}, w_{+1}, (w_{-2}, w_{-1}), (w_{-1}, w_{+1}), (w_{+1}, w_{+2}), (w_{-3}, w_{-2}, w_{-1}), (w_{-2}, w_{-1}, w_{+1}), (w_{-1}, w_{+1}, w_{+2}), (w_{+1}, w_{+2}, w_{+3}) \), with the part–of–speech information: \( p_{-3}, p_{-2}, p_{-1}, p_{+1}, p_{+2}, p_{+3} \), and, additionally, it incorporates broad context information: \( c_1 \cdots c_m \). SETB is intended to represent a more realistic set of attributes for WSD.

Note that \( c_i \) attributes are binary–valued, denoting the presence or absence of a content word in the sentence context.

The right hand–side of table 1 contains the information about the number of features. Note that SETA has a constant number of attributes (7), while for SETB this number depends on the concrete word, and that it ranges from 2,641 to 6,428.

| Attribute | POS | Sens. | Exs. | MFS | SETA | SETB |
|-----------|-----|-------|------|-----|------|------|
| age       | n   | 4     | 493  | 62.1| 7    | 3,015|
| art       | n   | 5     | 405  | 46.7| 7    | 2,641|
| car       | n   | 5     | 1,381| 95.1| 7    | 4,719|
| child     | n   | 4     | 1,068| 80.9| 7    | 4,840|
| church    | n   | 4     | 373  | 63.1| 7    | 2,375|
| cost      | n   | 3     | 1,500| 87.3| 7    | 4,930|
| fail      | v   | 19    | 1,500| 70.1| 7    | 4,173|
| head      | n   | 14    | 870  | 36.9| 7    | 4,284|
| interest  | n   | 7     | 1,500| 45.1| 7    | 5,328|
| know      | v   | 8     | 1,500| 34.9| 7    | 5,301|
| line      | n   | 26    | 1,342| 21.9| 7    | 5,813|
| set       | v   | 19    | 1,311| 36.9| 7    | 5,749|
| speak     | v   | 5     | 517  | 69.1| 7    | 2,975|
| take      | v   | 30    | 1,500| 35.6| 7    | 6,428|
| work      | n   | 7     | 1,469| 31.7| 7    | 6,321|
| Avg. nouns | 8.6 | 1,040.1| 57.4| 7    | 4,935.0|
| verbs     | 17.9| 1,265.6| 46.6| 7    | 5,203.5|
| all       | 12.1| 1,115.5| 52.9| 7    | 5,036.0|

Two sets of attributes have been used, which will be referred to as SETA and SETB, respectively. Let \( \cdots \) be the be the context of consecutive words around the word \( w \) to be disambiguated. Attributes refer to this context as follows.

4 EXPERIMENTS

The comparison of algorithms has been performed in series of controlled experiments using exactly the same training and test sets for each method. The experimental methodology consisted on a 10–fold cross–validation. All accuracy/error rate figures appearing in the paper are averaged over the results of the 10 folds. The statistical tests of significance have been performed using a 10-fold cross validation paired Student’s t–test with a confidence value of: \( t_{9,0.975} = 2.262 \).

Exemplar–based algorithms are run several times using different number of nearest neighbours (1, 3, 5, 7, 10, 15, 20 and 25) and the results corresponding to the best choice are reported.

4.1 Using SETA

Table 2 shows the results of all methods and variants tested on the 15 reference words, using the SETA set of attributes: Most Frequent Sense (MFS), Naive Bayes (NB), Exemplar–based using Hamming distance (EB\( h \), variants, 5th to 9th columns), and Exemplar–based approach using the MVDM metric (EB\( c \), variants, 10th to 12th columns) are included. The best result for each word is printed in boldface. From these figures, several conclusions can be drawn:

- All methods significantly outperform the MFS classifier.
- Referring to the EB\( h \), EB\( h \) performs significantly better than EB\( h \), confirming the results of Ng [16] that values of \( k \) greater than one are needed in order to achieve good performance with the \( k \)-NN approach. Additionally, both example weighting (EB\( k, c \)) and attribute weighting (EB\( h, a \)) significantly improve EB\( h, c \). Further, the combination of both (EB\( h, a, c \)) achieves an additional improvement.
- The MVDM metric is superior to Hamming distance. The accuracy of EB\( c \) is significantly higher than those of any EB\( h \) variant. Unfortunately, the use of weighted examples does not lead to further improvement in this case. A drawback of using the MVDM metric is the computational overhead introduced by its calculation. Table 2 shows that EB\( h \) is fifty times faster than EB\( c \) using SETA.
- The Exemplar–based approach achieves better results than the Naive Bayes algorithm. This difference is statistically significant when comparing the EB\( c \) and EB\( c \) against NB.

4.2 Using SETB

The aim of the experiments with SETB is to test both methods with a realistic large set of features. Table 3 summarizes the results of these experiments.

Let’s now consider only NB and EB\( h \) (3rd and 5th columns). A very surprising result is observed: while NB achieves almost the same accuracy that in the previous experiment, the exemplar–based approach shows a very low performance. The accuracy of EB\( h \) drops 8.6 points from 6th column of table 2 to 5th column of table 3, and is only slightly higher than that of MFS.

In order to construct a real \( k \)-NN–based system for WSD, the \( k \) parameter should be estimated by cross–validation using only the training set [16]. However, in our case, this cross–validation is computationally expensive and was avoided.

The current programs are implemented using PERL–5.003 and they run on a SUN UltraSPARC–2 machine with 192MB of RAM.

Detailed results for each word are not included.
The problem is that the binary representation of the broad–context attributes is not appropriate for the k-NN algorithm. Such a representation leads to an extremely sparse vector representation of the examples, since in each example only a few words, among all possible, are observed. Thus, the examples are represented by a vector of about 5,000 0’s and only a few 1’s. In this situation two examples will coincide in the majority of the values of the attributes (roughly of about 5,000 0’s and only a few 1’s. In this situation two examples are observed. Thus, the examples are represented by a vector from which the following conclusions can be drawn.

- The PE approach reaches excellent results, improving by 10.6 points the accuracy of EB (see 5th and 7th columns of table 3).
- Further, the results obtained significantly outperform those obtained using SETA, indicating that the (careful) addition of richer attributes leads to more accurate classifiers. Additionally, the behaviour of the different variants is similar to that observed when using SETA, with the exception that the addition of attribute-weighting to the example-weighting (PEB\textsubscript{h,10,c,e}) seems no longer useful.
- PNB algorithm is at least as accurate as NB.
- Table 3 shows that the positive approach increases greatly the efficiency of the algorithms. The acceleration factor is 80 for NB and 15 for EB\textsubscript{h} (the calculation of EB\textsubscript{h} variants was simply not feasible working with the attributes of SETB).
- The comparative conclusions between the Bayesian and Exemplar–based approaches reached in the experiments using SETA also hold here. Further, the accuracy of PEB\textsubscript{h,7,c} is now significantly higher than that of PNB.

5 GLOBAL RESULTS

In order to ensure that the results obtained so far also hold on a realistic broad-coverage domain, the PNB and PE algorithms have been tested on the whole sense–tagged corpus, using both sets of attributes. This corpus contains about 192,800 examples of 121 nouns.
and 70 verbs. The average number of senses is 7.2 for nouns, 12.6 for verbs, and 9.2 overall. The average number of training examples is 933.9 for nouns, 938.7 for verbs, and 935.6 overall.

The results obtained are presented in Table 5. It has to be noted that the results of PEB\textsubscript{e} are using SET\textsubscript{B} were not calculated due to the extremely large computational effort required by the algorithm (see Table 6). Results are coherent to those reported previously, that is:

| POS   | MFS | PNB | PEB\textsubscript{n} | PEB\textsubscript{e} | PEB\textsubscript{a} |
|-------|-----|-----|-----------------------|-----------------------|-----------------------|
| nouns | 56.4| 66.8| 68.5                  | 70.2                  | 68.5                  |
| verbs | 48.7| 64.8| 65.3                  | 66.4                  | 68.6                  |
| all   | 53.2| 67.1| 67.2                  | 66.4                  | 68.6                  |

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• In SET\textsubscript{A}, the Exemplar–based approach using the MVDM metric is significantly superior to the rest.

• In SET\textsubscript{B}, the Exemplar–based approach using Hamming distance and example weighting significantly outperforms the Bayesian approach. Although the use of the MVDM metric could lead to better results, the current implementation is computationally prohibitive.

• Contrary to the Exemplar-based approach, Naive Bayes does not improve accuracy when moving from SET\textsubscript{A} to SET\textsubscript{B}, that is, the simple addition of attributes does not guarantee accuracy improvements in the Bayesian framework.

6 CONCLUSIONS

This work has focused on clarifying some contradictory results obtained when comparing Naive Bayes and Exemplar–based approaches to WSD. Different alternative algorithms have been tested using two different attribute sets on a large sense–tagged corpus. The experiments carried out show that Exemplar–based algorithms have generally better performance than Naive Bayes, when they are extended with example/attribute weighting, richer metrics, etc.

The reported experiments also show that the Exemplar–based approach is very sensitive to the representation of a concrete type of attributes, frequently used in Natural Language problems. To avoid this drawback, an alternative representation of the attributes has been proposed and successfully tested. Furthermore, this representation also improves the efficiency of the algorithms, when using a large set of attributes.

The test on the whole corpus allows us to estimate that, in a realistic scenario, the best tradeoff between performance and computational requirements is achieved by using the Positive Exemplar–based algorithm, SET\textsubscript{B} set of attributes, Hamming distance, and example–weighting.

Further research on the presented algorithms to be carried out in the near future includes: 1) The study of the behaviour with respect to the number of training examples; 2) The study of the robustness in the presence of highly redundant attributes; 3) The testing of the algorithms on alternative sense–tagged corpora automatically acquired from Internet.

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