Integrating a Lexical Database and a Training Collection for Text Categorization

José María Gómez-Hidalgo
Manuel de Buenaga Rodríguez
{jmgonz,mbuenaga}@dia.ucm.es
Departamento de Informática y Automática†
Universidad Complutense de Madrid
Avda. Complutense s/n, 28040 Madrid (Spain)

Abstract

Automatic text categorization is a complex and useful task for many natural language processing applications. Recent approaches to text categorization focus more on algorithms than on resources involved in this operation. In contrast to this trend, we present an approach based on the integration of widely available resources as lexical databases and training collections to overcome current limitations of the task. Our approach makes use of WordNet synonymy information to increase evidence for bad trained categories. When testing a direct categorization, a WordNet based one, a training algorithm, and our integrated approach, the latter exhibits a better performance than any of the others. Incidentally, WordNet based approach performance is comparable with the training approach one.

1 Introduction

Text categorization (TC) is the classification of documents with respect to a set of one or more pre-existing categories. TC is a hard and very useful operation frequently applied to the assignment of subject categories to documents, to route and filter texts, or as a part of natural language processing systems.

In this paper we present an automatic TC approach based on the use of several linguistic resources. Nowadays, many resources like training collections...
and lexical databases have been successfully employed for text classification tasks [1], but always in an isolated way. The current trend in the TC field is to pay more attention to algorithms than to resources. We believe that the key idea for the improvement of text categorization is increasing the amount of information a system makes use of, through the integration of several resources.

We have chosen the Information Retrieval vector space model for our approach. Term weight vectors are computed for documents and categories employing the lexical database WordNet and the training subset of the test collection Reuters-22173. We calculate the weight vectors for:

- A direct approach,
- a Wordnet based approach,
- a training collection approach,
- and finally, a technique for integrating WordNet and a training collection.

Later, we compare document-category similarity by means of a cosine-based function. We have driven a series of experiments on the test subset of Reuters-22173, which yields two conclusions. First, the integrated approach performs better than any of the other ones, confirming the hypothesis that the more informed a text classification system is, the better it performs. Secondly, the lexical database oriented technique can rival with the training approach, avoiding the necessity of cost-expensive building of training collections for any domain and classification task.

2 Task Description

Given a set of documents and a set of categories, the goal of a categorization system is to decide whether any document belongs to any category or not. The system makes use of the information contained in a document to compute a degree of pertinence of the document to each category. Categories are usually subject labels like ART or MILITARY, but other categories like text genres are also interesting [2]. Documents can be news stories, e-mail messages, reports, and so forth.

The most widely used resource for TC is the training collection. A training collection is a set of manually classified documents that allows the system to guess clues on how to classify new unseen documents. There are currently several TC test collections, from which a training subset and a test subset can be obtained. For instance, the huge TREC collection [3], OHSUMED [4] and Reuters-22173 [5] have been collected for this task. We have selected Reuters because it has been used in other work, facilitating the comparison of results.
Lexical databases have been rarely employed in TC, but several approaches have demonstrated their usefulness for term classification operations like word sense disambiguation \[6, 7\]. A lexical database is a reference system that accumulates information on the lexical items of one or several languages. In this view, machine readable dictionaries can also be regarded as primitive lexical databases. Current lexical databases include WordNet \[8\], EDR \[9\] and Roget’s Thesaurus. WordNet’s large coverage and frequent utilization has led us to use it for our experiments.

We organize our work depending on the kind and number of resources involved. First, a direct approach in which only the categories themselves are the terms used in representation has been tested. Secondly, WordNet by itself has been used for increasing the number of terms and so, the amount of predicting information. Thirdly, we have made use of the training subset of Reuters to obtain the categories representatives. Finally, we have employed both WordNet and Reuters to get a better representation of undertrained categories.

3 Integrating Resources in the Vector Space Model

The Vector Space Model (VSM) \[10\] is a very suitable environment for expressing our approaches to TC: it is supported by many experiences in text retrieval \[11, 12\]; it allows the seamless integration of multiple knowledge sources for text classification; and it makes it easy to identify the role of every knowledge source involved in the classification operation. In the next sections we present a straightforward adaptation of the VSM for TC, and the way we use the chosen resources for calculating several model elements.

3.1 Vector Space Model for Text Categorization

The bulk of the VSM for Information Retrieval (IR) is representing natural language expressions as term weight vectors. Each weight measures the importance of a term in a natural language expression, which can be a document or a query. Semantic closeness between documents and queries is computed by the cosine of the angle between document and query vectors.

Exploiting an obvious analogy between queries and categories, the latters can be represented by term weight vectors. Then, a category can be assigned to a document when the cosine similarity between them exceeds a certain threshold, or when the category is highly ranked. In a closer look, and given three sets of \( N \) terms, \( M \) documents and \( L \) categories, the weight vector for document \( j \) is \( \langle w_{d1j}, w_{d2j}, \ldots, w_{dNj} \rangle \) and the weight vector for category \( k \) is \( \langle w_{c1k}, w_{c2k}, \ldots, w_{cNk} \rangle \). The similarity between document \( j \) and category \( k \) is
obtained with the formula:

$$sim(d_j, c_k) = \frac{\sum_{i=1}^{N} wd_{ij} \cdot wc_{ik}}{\sqrt{\sum_{i=1}^{N} w^2 d_{ij} \cdot \sum_{i=1}^{N} w^2 c_{ik}}}$$

Term weights for document vectors can be computed using well-known formulae based on term frequency. We use the following one from [11]:

$$wd_{ij} = tf_{ij} \cdot \log_2 \frac{M}{df_i}$$

Where $tf_{ij}$ is the frequency of term $i$ in document $j$, and $df_i$ is the number of documents in which term $i$ occurs. Now, only weights for category vectors are to be obtained. Next we will show how to do it depending on the resource used.

### 3.2 Direct Approach

This approach to TC makes no use of any resource apart from the documents to be classified. It tests the intuition that the name of content-based categories is a good predictor for the occurrence of these categories. For instance, the occurrence of the word “barley” in a document suggests that this one should be classified in the barley category. We have taken exactly the categories names, although classification in more general categories like strategic-metal should rather rely on the occurrence of more specific words like “gold” or “zinc.”

In this approach, the terms used for the representation are just the categories themselves. The weight of term $i$ in the vector for category $k$ is 1 if $i = k$ and 0 in other cases. Multiword categories imply the use of multiword terms. For example, the expression “balance of payments” is considered as one term. When categories consist of several synonyms (like iron-steel), all of them are used in the representation. Since the number of categories in Reuters is 135, and two of them are composite, this approach produces 137-component vectors.

### 3.3 WordNet-based Approach

Lexical databases contain many kinds of information (concepts; synonymy and other lexical relations; hyponymy and other conceptual relations; etc.). For instance, WordNet represents concepts as synonym sets, or synsets. We have selected this synonymy information, performing a “category expansion” similar

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1 All the following examples are taken from the Reuters category set and involve words that actually occur in the documents.
to query expansion in IR. For any category, the synset it belongs to is selected, and any other term belonging to it is added to the representation. This technique increases the amount of evidence used to predict category occurrence.

Unfortunately, the disambiguation of categories with respect to WordNet concepts is required. We have performed this task manually, because the small number of categories in the test collection made it affordable. We are currently designing algorithms for automating this operation.

After locating categories in WordNet, a term set containing all the category’s synonyms has been built. For the 135 categories used in this study, we have produced 368 terms. Although some meaningless terms occur and could be deleted, we have developed no automatic criteria for this at the moment.

Let us take a look to one example. The fuel category has driven us to the addition of the terms “combustible” and “combustible material,” since they belong to the same synset in WordNet. In general, the term weight vector for category $k$ is 1 for every synonym of the category and 0 for any other term.

### 3.4 Training Collection Approach

The key assumption when using a training collection is that a term often occurring within a category and rarely within others is a good predictor for that category. A set of predictors is typically computed from term to category co-occurrence statistics, as a training step. The computation depends on the approach and algorithm selected. As Lewis has done before, we have replicated in the VSM early Bayesian experiments that had reported good results.

Terms are selected according to the number of times they occur within categories. Those terms which co-occur at least with the 1% and at most with the 10% of the categories are taken. Among them, those 286 with higher document frequency are selected. We work the weights out in the same way as in documents vectors:

$$w_{ci} = tf_{ik} \cdot \log_2 \frac{L}{cf_i}$$

Where $tf_{ik}$ is the number of times that term $i$ occurs within documents assigned to category $k$, and $cf_i$ is the number of categories within term $i$ occurs. For example, after selecting and weighting categories, the high-frequency term “export” shows its largest weight for category TRADE, but it also shows large weights for GRAIN or WHEAT, and small weights for BELGIAN-FRANC and WOOL. A less frequent term typically provides evidence for a smaller number of categories. For example, “private” has a large weight only for ACQUISITION, and medium for EARNINGS and TRADE.
3.5 Integrating WordNet and a Training Collection

Several ways of integrating WordNet and Reuters have occurred to us. A sensible one is to use concepts instead of terms as representatives. However, and although promising, Voorhees reported no improvements with this idea [12]. On the other side, we have realized that the shortcomings in training can be corrected using WordNet to provide better forecast of low frequency categories.

In general, we have linked WordNet weight vectors to training weight vectors. First we have removed those WordNet terms not occurring in the training collection. Then we have normalized both WordNet vectors and training vectors to separately add up across each category. This way we have smoothed training weights (much larger than WordNet ones), giving equal influence to each kind of term weight. This technique results in 461 term weights vectors, 185 coming from WordNet, and 286 from training. Weights for terms occurring in both sets have been summed. Examples of terms coming from training are “import” or “government,” with high weights for highly frequent categories, like ACQ (acquisition). Examples of terms coming from WordNet are “petroleum” or “peanut,” with weights only for the corresponding categories CRUDE and GROUNDNUT respectively.

We can clearly identify the role of each resource in this TC approach. WordNet supplies information on the semantic relatedness of terms and categories when training data is no longer available or reliable. It directly contributes with part of the terms used in the vector representation. On the other side, the training collection supplies terms for those categories that are better trained. The problem of unavailability of training data is then overcome through the use of an external resource.

4 Evaluation

Evaluation of TC and other text classification operations exhibits great heterogeneity. Several metrics and test collections have been used for different approaches or works. This results in a lack of comparability among the approaches, forcing to replicate experiments from other researchers. Trying to minimize this problem, we have chosen a set of very extended metrics and a frequently used free test collection for our work. The metrics are recall and precision, and the test collection is, as introduced before, Reuters-22173. Before stepping into the actual results, we provide a closer look to these elements.

4.1 Evaluation metrics

The VSM promotes recall and precision based evaluation, but there are several ways of calculating or even defining them. We focus on recall, being the...
discussion analogous for precision. First, definition can be given regarding categories or documents \cite{3}. Second, computation can be done macro-averaging or micro-averaging \cite{4}.

- Recall can be defined as the number of correctly assigned documents to a category over the number of documents to be correctly assigned to the category. But a document-oriented definition is also possible: the number of correctly assigned categories to a document over the number of correct categories to be assigned to the document. This later definition is more coherent with the task, but the former allows to identify the most problematic categories.

- Macro-averaging consists of computing recall and precision for every item (document or category) in one of both previous ways, and averaging after it. Micro-averaging is adding up all numbers of correctly assigned items, items assigned, and items to be assigned, and calculate only one value of recall and precision. When micro-averaging, no distinction about document or category orientation can be made. Macro-averaging assigns equal weight to every category, while micro-averaging is influenced by most frequent categories.

Evaluation depends finally on the category assignment strategy: probability thresholding, \textit{k-per-doc} assignment, etc. Strategies define the way to produce recall/precision tables. For instance, if similarities are normalized to the [0, 1] interval, eleven levels of probability threshold can be set to 0.0, 0.1, and so. When the system performs \textit{k-per-doc} assignment, the value of \textit{k} is ranged from 1 to a reasonable maximum.

We must assign an unknown number of categories to each document in Reuters. So, the probability thresholding approach seems the most sensible one. We have then computed recall and precision for eleven levels of threshold, both macro and micro-averaging. When macro-averaging, we have used the category-oriented definition of recall and precision. After that, we have calculated averages of those eleven values in order to get single figures for comparison.

4.2 The Test Collection

The Reuters-22173 collection consists of 22,173 newswire articles from Reuters collected during 1987. Documents in Reuters deal with financial topics, and were classified in several sets of financial categories by personnel from Reuters Ltd. and Carnegie Group Inc. Documents vary in length and number of categories assigned, from 1 line to more than 50, and from none categories to more than 8. There are five sets of categories: TOPICS, ORGANIZATIONS, EXCHANGES, PLACES, and PEOPLE. As others before, we have selected the 135 TOPICS for our experiments. An example of news article classified in \textit{BOP} (balance of
ITALIAN BALANCE OF PAYMENTS IN DEFICIT IN MAY

ROME, June 18 - Italy's overall balance of payments showed a deficit of 3,211 billion lire in May compared with a surplus of 2,040 billion in April, provisional Bank of Italy figures show.

The May deficit compares with a surplus of 1,555 billion lire in the corresponding month of 1986.

For the first five months of 1987, the overall balance of payments showed a surplus of 299 billion lire against a deficit of 2,854 billion in the corresponding 1986 period.

REUTER

Figure 1: Document number 6505 from Reuters.

payments) and TRADE is shown in Figure 1. Some spurious formatting has been removed from it.

When a test collection is provided, it is customary to divide it into a training subset and a test subset. Several partitions have been suggested for Reuters, among which ones we have opted for the most general and difficult one. First 21,450 news stories are used for training, and last 723 are kept for testing. We summarize significative differences between test and training sets in Figure 2. These differences can bring noise into categorization, because training relies on similarity between training and test documents. Nevertheless, this 21,450/723 partition has been used before and involves the general case of documents with no categories assigned.

We have worked with raw data provided in the Reuters distribution. Control characters, numbers and several separators like ‘/’ have been removed, and categories different from the TOPICS set have been ignored. For disambiguating categories with respect to WordNet senses, we first had to acquire their meaning, not always self-evident. This task has been performed by direct examination of training documents.
4.3 Results and Interpretation

The results of our first series of experiments are summarized in the table in Figure 3. This table shows recall and precision averages calculated both macro and micro-averaging for a threshold-based assignment strategy. Values for the integrated approach show some general advantage over WORDNET and training approaches, but results are not decisive. Training results are comparable with those from Lewis [5], and the WORDNET approach is roughly equivalent to the training one.

On one hand, the integrated approach shows a better performance than the WORDNET one in general, although a problem of precision is detected when macro-averaging. The influence of low precision training has produced this effect. We are planning to strengthen WORDNET influence to overcome this problem.

On the other hand, the integrated approach reports better general performance than the training approach.

As expected, WORDNET and training both beat the direct approach. When comparing WORDNET and training approaches, we observe that the former produces better results with categories of low frequency, while the latter performs better in highly frequent categories. However, both exhibit the same overall
behaviour. Differences in categories are noticed by the fact that micro-averaging is influenced by highly frequent elements, while macro-averaging depends on the results of many elements of low frequency.

5 Related Work

Text categorization has emerged as a very active field of research in the recent years. Many studies have been conducted to test the accuracy of training methods, although much less work has been developed in lexical database methods. However, lexical databases and especially WORDNET have been often used for other text classification tasks, like word sense disambiguation.

Many different algorithms making use of a training collection have been used for TC, including \textit{k-nearest-neighbor} algorithms \cite{13}, Bayesian classifiers \cite{5}, learning algorithms based in relevance feedback \cite{16} or in decision trees \cite{17}, or neural networks \cite{18}. Apart from \cite{5}, the closest approach to ours is the one from Larkey and Croft \cite{13}, who combine \textit{k-nearest-neighbor}, Bayesian independent and relevance feedback classifiers, showing improvements over the separated approaches. Although they do not make use of several resources, their approach tends to increase the information available to the system, in the spirit of our hypothesis.

To our knowledge, lexical databases have been used only once in TC. Hearst \cite{19} adapted a disambiguation algorithm by Yarowsky using WORDNET to recognize category occurrences. Categories are made of WORDNET terms, which is not the general case of standard or user-defined categories. It is a hard task to adapt WORDNET subsets to pre-existing categories, especially when they are domain dependent. Hearst’s approach shows promising results confirmed by the fact that our WORDNET-based approach performs at least equally to a simple training approach.

Lexical databases have been employed recently in word sense disambiguation. For example, Agirre and Rigau \cite{7} make use of a semantic distance that takes into account structural factors in WORDNET for achieving good results for this task. Additionally, Resnik \cite{6} combines the use of WORDNET and a text collection for a definition of a distance for disambiguating noun groupings. Although the text collection is not a training collection (in the sense of a collection of manually labelled texts for a pre-defined text processing task), his approach can be regarded as the most similar to ours in the disambiguation task. Finally, Ng and Lee \cite{20} make use of several sources of information inside a training collection (neighborhood, part of speech, morphological form, etc.) to get good results in disambiguating unrestricted text.

We can see, then, that combining resources in TC is a new and promising approach supported by previous research in this and other text classification operations. With more information extracted from WORDNET and better training algorithms, automatic TC integrating several resources could compete with
manual indexing in quality, and beat it in cost and efficiency.

6 Conclusions and Future Work

In this paper, we have presented a multiple resource approach for TC. This approach integrates the use of a lexical database and a training collection in a vector space model for TC. The technique is based on improving the language of representation construction through the use of the lexical database, which overcomes training deficiencies. We have tested our approach against training algorithms and lexical database algorithms, reporting better results than both of these techniques. We have also acknowledged that a lexical database algorithm can rival training algorithms in real world situations.

Two main work lines are open: first, we have to conduct new series of experiments to check the lexical database and the combined approaches with other more sophisticated training approaches; second, we will extend the multiple resource technique to other text classification tasks, like text routing or relevance feedback in text retrieval.

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