Bridging Languages through Etymology: The case of cross language text categorization

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Abstract
We propose the hypothesis that word etymology is useful for NLP applications as a bridge between languages. We support this hypothesis with experiments in cross-language (English-Italian) document categorization. In a straightforward bag-of-words experimental set-up we add etymological ancestors of the words in the documents, and investigate the performance of a model built on English data, on Italian test data (and viceversa). The results show not only statistically significant, but a large improvement – a jump of almost 40 points in F1-score – over the raw (vanilla bag-of-words) representation.

1 Introduction
When exposed to a document in a language he does not know, a reader might be able to glean some meaning from words that are the same (e.g. names) or similar to those in a language he knows. As an example, let us say that an Italian speaker is reading an English text that contains the word expense, which he does not know. He may be reminded however of the Latin word expensa which is also the etymological root of the Italian word spesa, which usually means “cost”/“shopping”, and may thus infer that the English word refers to the cost of things. In the experiments presented here we investigate whether an automatic text categorization system could benefit from knowledge about the etymological roots of words. The cross language text categorization (CLTC) task consists of categorizing documents in a target language $L_t$ using a model built from labeled examples in a source language $L_s$. The task becomes more difficult when the data consists of comparable corpora in the two languages – documents on the same topics (e.g. sports, economy) – instead of parallel corpora – there exists a one-to-one correspondence between documents in the corpora for the two languages, one document being the translation of the other.

To test the usefulness of etymological information we work with comparable collections of news articles in English and Italian, whose articles are assigned one of four categories: culture and school, tourism, quality of life, made in Italy. We perform a progression of experiments, which embed etymological information deeper and deeper into the model. We start with the basic set-up, representing the documents as bag-of-words, where we train a model on the English training data, and use this model to categorize documents from the Italian test data (and viceversa). The results are better than random, but quite low. We then add the etymological roots of the words in the data to the bag-of-words, and notice a large – 21 points – increase in performance in terms of F1-score. We then use the bag-of-words representation of the training data to build a semantic space using LSA, and use the generated word vectors to represent the training and test data. The improvement is an additional 16 points in F1-score.

Compared to related work, presented in Section 3, where cross language text categorization is approached through translation or mapping of features (i.e. words) from the source to the target language, word etymologies are a novel source of cross-lingual knowledge. Instead of mapping features between languages, we introduce new features which are shared, and thus do not need translation or other forms of mapping.

The experiments presented show unequivocally that word etymology is a useful addition to computational models, just as they are to readers who have such knowledge. This is an interesting and useful result, especially in the current research landscape where using and exploiting multi-linguality is a desired requirement.
2 Word Etymology

Word etymology gives us a glimpse into the evolution of words in a language. Words may be adopted from a language because of cultural, scientific, economic, political or other reasons (Hitchings, 2009). In time these words “adjust” to the language that adopted them – their sense may change to various degrees – but they are still semantically related to their etymological roots. To illustrate the point, we show an example that the reader, too, may find amusing: on the ticket validation machine on Italian buses, by way of instruction, it is written *Per obliterare il biglietto ...*. A native/frequent English speaker would most probably key in on, and be puzzled by, the word *obliterare*, very similar to the English *obliterate*, whose most used sense is *to destroy completely / cause to physically disappear*. The Italian *obliterare* has the “milder” sense of *cancellare – cancel* (which is also shared by the English *obliterate*, but is less frequent according to Merriam-Webster), and both come from the Latin *obliterare* – erase, efface, cause to disappear. While there has been some sense migration – in English the more (physically) destructive sense of the word has higher prominence, while in Italian the word is closer in meaning to its etymological root – the Italian and the English words are still semantically related.

Dictionaries customarily include etymological information for their entries, and recently, Wikipedia’s Wiktionary has joined this trend. The etymological information can, and indeed has been extracted and prepared for machine consumption (de Melo and Weikum, 2010): Etymological WordNet\(^1\) contains 6,031,431 entries for 2,877,036 words (actually, morphemes) in 397 languages. A few sample entries from this resource are shown in Figure 1.

The information in Etymological WordNet is organized around 5 relations: *etymology* with its inverse *etymological origin of*; *is derived from* with its inverse *has derived form*; and the symmetrical *etymologically related*. The etymology relation links a word with its etymological ancestors, and it is the relation used in the experiments presented here. Prefixes and suffixes – such as *ex-* and *-ly* shown in Figure 1 – are filtered out, as they bring in much noise by relating words that merely share such a morpheme (e.g. *absurdly* and *admirably*) but are otherwise semantically distant. *Has derived form* is also used, to capture morphological variations.

The depth of the etymological hierarchy (considering the *etymology* relations) is 10. Figure 1 shows an example of a word with several levels of etymological ancestry.

\(^1\)http://www1.icsi.berkeley.edu/~demelo/etymwn/
Text categorization (also text classification), “the task of automatically sorting a set of documents into categories (or classes or topics) from a predefined set” (Sebastiani, 2005), allows for the quick selection of documents from the same domain, or the same topic. It is a very well research area, dating back to the 60s (Borko and Bernick, 1962). The most frequently, and successfully, used document representation is the bag-of-words (BoWs). Results using this representation achieve accuracy in the 90%s. Most variations include feature filtering or weighing, and variations in learning algorithms (Sebastiani, 2005).

Within the area of cross-language text categorization (CLTC) several methods have been explored for producing the model for a target language $L_t$ using information and data from the source language $L_s$. In a precursor task to CLTC, cross language information retrieval (CLIR), Du mais et al. (1997) find semantic correspondences in parallel (different language) corpora through latent semantic analysis (LSA). Most CLTC methods rely heavily on machine translation (MT). MT has been used: to cast the cross-language text categorization problem to the monolingual setting (Fortuna and Shawe-Taylor, 2005); to cast the cross-language text categorization problem into two monolingual settings for active learning (Liu et al., 2012); to translate and adapt a model built on language $L_s$ to language $L_t$ (Rigutini et al., 2005), (Shi et al., 2010); to produce parallel corpora for multi-view learning (Guo and Xiao, 2012). Wan et al. (2011) also use machine translation, but enhance the processing through domain adaptation by feature weighing, assuming that the training data in one language and the test data in the other come from different domains, or can exhibit different linguistic phenomena due to linguistic and cultural differences. Prettenhofer and Stein (2010) use a word translation oracle to produce pivots – pairs of semantically similar words – and use the data partitions induced by these words to find cross language structural correspondences.

In a computationally lighter framework, not dependent on MT, Gliozzo and Strapparava (2006) and Wu et al. (2008) use bilingual lexicons and aligned WordNet synsets to obtain shared features between the training data in language $L_s$ and the testing data in language $L_t$. Gliozzo and Strapparava (2005), the first to use comparable as op-

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### Figure 2: Multilingual word-by-document matrix

|                | English texts |         | Italian texts |
|----------------|--------------|---------|---------------|
|                | $t_1$ | $t_2$ | ... | $t_{m-1}$ | $t_m$ | $t_1'$ | $t_2'$ | ... | $t_{m-1}'$ | $t_m'$ |
| **English Lexicon** | $w_1$ | 0 | 1 | ... | 0 | 1 | 0 | 1 | ... | 0 | 1 |
|                | $w_2$ | 1 | 1 | ... | 1 | 0 | 0 | 0 | ... | 0 | 0 |
|                | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
|                | $w_{n-1}$ | 0 | 1 | ... | 0 | 0 | ... | 0 | ... | 0 | 0 |
|                | $w_n$ | 0 | 1 | ... | 0 | 0 | ... | 0 | ... | 0 | 0 |
| **shared names and words** | $u_1^{ex}$ | 1 | 0 | ... | 0 | 0 | ... | 0 | ... | 0 | 1 |
|                | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **common etymology** | $u_1^{et}$ | 0 | 1 | ... | 0 | 0 | ... | 1 | 0 | ... | 1 |
|                | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **Italian Lexicon** | $w_1$ | 0 | 0 | ... | 0 | 1 | ... | 1 | 1 | ... | 1 |
|                | $w_2$ | 0 | 0 | ... | 0 | 0 | ... | 0 | ... | 0 | 1 |
|                | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
|                | $w_{n-1}$ | ... | ... | ... | ... | ... | ... | ... | ... | ... | 0 |
|                | $w_n$ | ... | ... | ... | ... | ... | ... | ... | ... | ... | 0 |

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### 3 Cross Language Text Categorization

Text categorization (also text classification), “the task of automatically sorting a set of documents into categories (or classes or topics) from a predefined set” (Sebastiani, 2005), allows for the quick selection of documents from the same domain, or the same topic. It is a very well research area, dating back to the 60s (Borko and Bernick, 1962). The most frequently, and successfully, used document representation is the bag-of-words (BoWs). Results using this representation achieve accuracy in the 90%s. Most variations include feature filtering or weighing, and variations in learning algorithms (Sebastiani, 2005).

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posed to parallel corpora for CLTC, use LSA to build multilingual domain models.

The bag-of-word document representation maps a document \( d_i \) from a corpus \( D \) into a \( k \)-dimensional space \( \mathbb{R}^k \), where \( k \) is the dimension of the (possibly filtered) vocabulary of the corpus: \( W = \{ w_1, \ldots, w_k \} \). Position \( j \) in the vector representation of \( d_i \) corresponds to word \( w_j \), and it may have different values, among the most commonly used being: binary values – \( w_j \) appears (1) or not (0) in \( d_i \); frequency of occurrence of \( w_j \) in \( d_i \), absolute or normalized (relative to the size of the document or the size of the vocabulary); the \( tf \times idf(w_j, d_i, D) \)

For the task of cross language text categorization, the problem of sharing a model across languages is that the dimensions, a.k.a the vocabulary, of the two languages are largely different. Limited overlap can be achieved through shared names and words. As we have seen in the literature review, machine translation and bilingual dictionaries can be used to cast these dimensions from the source language \( L_s \) to the target language \( L_t \). In this work we explore expanding the shared dimensions through word etymologies. Figure 2 shows schematically the binary \( k \)-dimensional representation for English and Italian data, and shared dimensions.

Cross language text categorization could be used to obtain comparable corpora for building translation models. In such a situation, relying on a framework that itself relies on machine translation is not helpful. Bilingual lexicons are available for frequently studied languages, but less so for those poorer in resources. Considering such shortcomings, we look into additional linguistic information, in particular word etymology. This information impacts the data representation, by introducing new shared features between the different language corpora without the need for translation or other forms of mapping. The newly produced representation can be used in conjunction with any of the previously proposed algorithms.

Word etymologies are a novel source of linguistic information in NLP, possibly because resources that capture this information in a machine readable format are also novel. Fang et al. (2009) used limited etymological information extracted from the Collins English Dictionary (CED) for text categorization on the British National Corpus (BNC): information on the provenance of words (ranges of probability distribution of etymologies in different versions of Latin – New Latin, Late Latin, Medieval Latin) was used in a “home-made” range classifier.

The experiments presented in this paper use the bag-of-word document representation with absolute frequency values. To this basic representation we add word etymological ancestors and run classification experiments. We then use LSA – previously shown by (Dumais et al., 1997) and (Gliozzo and Strapparava, 2005) to be useful for this task – to induce the latent semantic dimensions of documents and words respectively, hypothesizing that word etymological ancestors will lead to semantic dimensions that transcend language boundaries. The vectors obtained through LSA (on the training data only) for words that are shared by the English training data and the Italian test data (names, and most importantly, etymological ancestors of words in the original documents) are then used for representing the training and test data. The same process is applied for Italian training and English test data. Classification is done using support vector machines (SVMs).

3.1 Data

The data we work with consists of comparable corpora of news articles in English and Italian. Each news article is annotated with one of the four categories: culture_and_school, tourism, quality_of_life, made_in_Italy. Table 1 shows the dataset statistics. The average document length is approximately 300 words.

3.2 Raw cross-lingual text categorization

As is commonly done in text categorization (Sebastiani, 2005), the documents in our data are represented as bag-of-words, and classification is done using support vector machines (SVMs).

One experimental run consists of 4 binary experiments – one class versus the rest, for each of the 4 classes. The results are reported through micro-averaged precision, recall and F1-score for the targeted class, as well as overall accuracy. The high results, on a par with text categorization experiments in the field, validates our experimental set-up.

For the cross language categorization experiments described in this paper, we use the data described above, and train on one language (English/Italian), and test on the other, using the same
### Table 1: Dataset statistics

| Categories             | English |               | Italian |               |
|------------------------|---------|---------------|---------|---------------|
|                        | Training Test Total | Training Test Total |         |               |
| quality_of_life        | 5759 1989 7748     | 5781 1901 7682   |         |               |
| made_in_Italy          | 5711 1864 7575     | 6111 2068 8179   |         |               |
| tourism                | 5731 1857 7588     | 6090 2015 8105   |         |               |
| culture_and_school     | 3665 1245 4910     | 6284 2104 8388   |         |               |
| Total                  | 20866 6955 27821   | 24266 8088 32354 |         |               |

### Table 2: Performance for monolingual raw text categorization

|              | Prec | Rec | F1  | Acc  |
|--------------|------|-----|-----|------|
| Train EN / Test EN | 0.92 | 0.92 | 0.92 | 0.96 |
| Train IT / Test IT   | 0.94 | 0.94 | 0.94 | 0.97 |

### Table 3: Feature expansion with word etymologies

| expansion | training data vocabulary size | vocabulary overlap with testing |
|-----------|-------------------------------|---------------------------------|
| Train EN / Test IT |                               |
| raw       | 71122                         | 14207 (19.9%)                   |
| depth 1   | 78936                         | 18275 (23.1%)                   |
| depth 2   | 79068                         | 18359 (23.2%)                   |
| depth 3   | 79100                         | 18380 (23.2%)                   |
| depth 4   | 79103                         | 18382 (23.2%)                   |
| Train IT / Test EN |                               |
| raw       | 78750                         | 14110 (17.9%)                   |
| depth 1   | 83656                         | 18682 (22.3%)                   |
| depth 2   | 83746                         | 18785 (22.4%)                   |
| depth 3   | 83769                         | 18812 (22.5%)                   |
| depth 4   | 83771                         | 18814 (22.5%)                   |

3.3 Enriching the bag-of-word representation with word etymology

As personal experience has shown us that etymological information is useful for comprehending a text in a different language, we set out to test whether this information can be useful in an automatic processing setting. We first verified whether the vocabularies of our two corpora, English and Italian, have shared word etymologies. Relying on word etymologies from the Etymological dictionary, we found that from our data’s vocabulary, 518 English terms and 543 Italian terms shared 490 direct etymological ancestors. Etymological ancestors also help cluster related terms within one language – 887 etymological ancestors for 4727 English and 864 ancestors for 5167 Italian terms. This overlap further increases when adding derived forms (through the has-derived-form relation). The fact that this overlap exists strengthens the motivation to try using etymological ancestors for the task of text categorization.

In this first step of integrating word etymology into the experiment, we extract for each word in each document in the dataset its ancestors from the Etymological dictionary. Because each word $w_j$ in a document $d_i$ has associated an absolute frequency value $f_{ij}$ (the number of occurrences of $w_j$ in $d_i$), for the added etymological ancestors $e_k$ in document $D_i$ we associate as value the sum of frequencies of their etymological children in $d_i$: $f_{ie_k} = \sum_{w_j \in d_i} f_{ij}$.

We make the depth of extraction a parameter, and generate data representation when considering only direct etymological antecedents (depth 1) and then up to a distance of N. For our dataset we noticed that the representation does not change after N=4, so this is the maximum depth we consider. The bag-of-words representation for each document is expanded with the corresponding etymological features.
tutes. The increase is largest when introducing
the immediate etymological ancestors, of approx-
imately 4000 new (overlapping) features for both
combinations of training and testing. Without ety-
mo logical features the overlap was approximately
14000 for both configurations. The results ob-
tained with this enriched BoW representation for
etymological ancestor depth 1, 2 and 3 are pre-
presented in Figure 4.

3.4 Cross-lingual text categorization in a
latent semantic space adding etymology

Shared word etymologies can serve as a bridge be-	ween two languages as we have seen in the pre-
vious configuration. When using shared word ety-
mo logicals in the bag-of-words representation, we
only take advantage of the shallow association be-
tween these new features and the classes within
which they appear. But through the co-occurrence
of the etymological features and other words in
different documents in the training data, we can
induce a deeper representation for the words in
a document, that captures better the relationship
between the features (words) and the classes to
which the documents belong. We use latent se-
matic analysis (LSA) (Deerwester et al., 1990)
to perform this representational transformation.
The process relies on the assumption that word
co-occurrences across different documents are the
surface manifestation of shared semantic dimen-
sions. Mathematically, the (word × document)
matrix $D$ is expressed as a product of three ma-
trices:

$$ D = V \Sigma U^T $$

by performing singular value decomposition
(SVD). $V$ would correspond roughly to a (word
× latent semantic dimension) matrix, $U^T$ is the
transposed of a (document × latent semantic
dimension) matrix, and $\Sigma$ is a diagonal matrix
whose values are indicative of the “strength” of the
semantic dimensions. By reducing the size of $\Sigma$,
for example by selecting the dimensions with the
top $K$ values, we can obtain an approximation of
the original matrix $D \approx D_K = V_K \Sigma_K U_K^T$, where
we restrict the latent semantic dimensions taken
into account to the $K$ chosen ones. Figure 3 shows
schematically the process.

We perform this decomposition and dimension
reduction step on the (word × document) ma-
trix built from the training data only, and using
$K=400$. Both the training and test data are then
re-represented through the new word vectors from
matrix $V_K$. Because the LSA space was built only
from the training data, only the shared words and
shared etymological ancestors are used to produce
representations of the test data. The categorization
is done again with SVM. The results of this exper-
iment are shown in Figure 4, together with an LSA
baseline – using the raw data and relying on shared
words and names as overlap.

4 Discussion

The experiments whose results we present here
were produced using unfiltered data – all words in
the datasets, all etymological ancestors up to the
desired depth, no filtering based on frequency of
occurrence. Feature filtering is commonly done in
machine learning when the data has many features,
and in text categorization when using the bag-of-
words representation in particular. We chose not to
perform this step for two main reasons: (i) filter-
ing is sensitive to the chosen threshold; (ii) LSA
thrive s on word co-occurrences, which would be
drastically reduced by word removal. The point
that etymology information is a useful addition to
the task of cross-language text categorization can
be made without finding the optimal filtering set-
up.

The baseline experiments show that despite
the relatively large word overlap (approx. 14000
terms), cross-language text categorization gives
low results. Adding a first batch of etymological
information – approximately 4000 shared immedi-
ate ancestors – leads to an increase of 18 points in
terms of F1-score on the BoW experimental set-up
for English training/Italian testing, and 21 points
for Italian training/English testing. Further addi-
tions of etymological ancestors at depths 2 and
3 results in an increase of 21 points in terms of
F1-score for English training/Italian testing, and
27 points for Italian training/English testing. The
higher increase in performance on this experimen-
tal configuration for Italian training/English test-
ing is explained by the higher term overlap be-
between the training and test data, as evidenced by the statistics in Table 3.

The next processing step induced a representation of the shared words that encodes deeper level dependencies between words and documents based on word co-occurrences in documents. The LSA space built on the training data leads to a vector representation of the shared words, including the shared etymological ancestors, that captures more than the obvious word-document co-occurrences. Using this representation leads to a further increase of 15 points in F1-score for English training/Italian testing set-up over the BoW representation, and 14 points over the baseline LSA-based categorization. The increase for the Italian training/English testing is 5 points over the BoW representation, but 20 points over the baseline LSA. We saw that the high performance BoW on Italian training/English testing is due to the high term overlap. The clue to why the increase when using LSA is lower than for English training/Italian testing is in the way LSA operates – it relies heavily on word co-occurrences in finding the latent semantic dimensions of documents and words. We expect then that in the Italian training collection, words are “less shared” among documents, which means a lower average document frequency. Figure 5 shows the changes in average document frequency for the two training collections, starting with the raw data (depth 0), and with additional etymological features.

Figure 5: Document frequency changes with the addition of etymological features

The shape of the document frequency curves mirror the LSA results – the largest increase is the effect of adding the set of direct etymological ancestors, and additions of further, more distant, ancestors lead to smaller improvements.
We have performed the experiments described above on two releases of the Etymological dictionary. The results described in the paper were obtained on the latest release (February 2013). The difference in results on the two dictionary versions was significant: a 4 and 5 points increase respectively in micro-averaged F1-score in the bag-of-words setting for English training/Italian testing and Italian training/English testing, and a 2 and 6 points increase in the LSA setting. This indicates that more etymological information is better, and the dynamic nature of Wikipedia and the Wiktionary could lead to an ever increasing and better etymological resource for NLP applications.

5 Conclusion

The motivation for this work was to test the hypothesis that information about word etymology is useful for computational approaches to language, in particular for text classification. Cross-language text classification can be used to build comparable corpora in different languages, using a single language starting point, preferably one with more resources, that can thus spill over to other languages. The experiments presented have shown clearly that etymological ancestors can be used to provide the necessary bridge between the languages we considered – English and Italian. Models produced on English data when using etymological information perform with high accuracy (89%) and high F1-score (80) on Italian test data, with an increase of almost 40 points over a simple bag-of-words model, which, for crossing language boundaries, relies exclusively on shared names and words. Training on Italian data and testing on English data performed almost as well (87% accuracy, 75 F1-score). We plan to expand our experiments to more languages with shared etymologies, and investigate what characteristics of languages and data indicate that etymological information is beneficial for the task at hand.

We also plan to explore further uses for this language bridge, at a finer semantic level. Monolingual and cross-lingual textual entailment in particular would be interesting applications, because they require finding shared meaning on two text fragments. Word etymologies would allow recognizing words with shared ancestors, and thus with shared meaning, both within and across languages.

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