Native Language Detection
with 'Cheap' Learner Corpora

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Abstract

We begin by showing that the best publicly available, multiple-L1 learner corpus, the *International Corpus of Learner English* (Granger et al. 2009), has serious issues when used for the task of native language detection (NLD). The topic biases in the corpus are a confounding factor that result in crossvalidated performance that is misleading, for all the feature types which are traditionally used. Our approach here is to look for other, cheap ways to get training data for NLD. To that end, we present the web-scraped Lang-8 learner corpus, and show that it is useful for the task, particularly if large quantities of data are used. This also seems to facilitate the use of lexical features, which had been previously avoided. We also investigate ways to do NLD that don't involve having learner corpora at all, including double-translation and extracting information from L1 corpora directly. All of these avenues are shown to be promising.

Keywords: Native Language, Text Classification, Natural Language Processing, Learner Corpora

1.   Introduction

Native language detection (or identification), henceforth NLD, is the task of distinguishing the native language background (L1) of a non-native writer of a text. As a natural language processing (NLP) task, it is properly categorized as a form of text classification, the standard approach to which is machine learning classification using algorithms such as support vector machines (SVMs) (Witten & Frank 2005). Generally speaking, these algorithms learn associations between features and classifications from a corpus of texts whose classification is known, and then use that information to classify new texts. Therefore, having a (preferably large) corpus of training data is a necessary first step for any machine learning approach. For NLD, there is a paucity of training (and testing) corpora, since roughly comparable texts from multiple L1 backgrounds (for the same L2) are required. The only three text corpora, as far as we are aware, that are appropriate for use with multiple language NLD are the *International Corpus of Learner English* (Granger et al. 2009) or ICLE, the *Cambridge Learner Corpus* (Yannakoudakis et al. 2011), and the *Falko Corpus* (Lüdeling et al., 2008). Most work in NLD has been carried out in the first of these, since the second is not publicly available (except for a very small portion that has recently been released) and the third is smaller and in German (the other two are English corpora). When only one corpus is available, evaluation of NLD is often carried out using crossvalidation,

which involves building multiple models, training on one portion of the corpus and testing on another.

Koppel et al. (2005) was the first work in NLD to use the ICLE (version 1); they trained SVM models with a set of stylistic features, including POS and character *n*-grams (sequences), function words, and spelling error types, achieving 80% accuarcy in a 5-language task. Tsur & Rappoport (2007) focused on character *n*-grams; they were concerned about the effect of topic bias, and (attempted to) remove it by discarding prominent words, with 66% accuracy in the same set as Koppel et al. Wong & Dras (2009), working in ICLE v2, investigate particular kinds of syntactic error common to L1 backgrounds, but they failed to improve on Koppel et al. In recent work, Wong & Dras (2011) showed that generally syntactic patterns, as derived by a parser, are more effective than other stylistic features. The Cambridge Learner Corpus has been used recently by Kochmar (2011), who concluded that character *n*-grams are the most promising feature type, and Golcher & Reznicek (2011) used the Falko corpus to show that title (topic) classification and NLD are more closely linked than previously assumed.

In Section 2 of this paper, we will begin by showing that the ICLE is problematic as a corpus for NLD because of topic bias in the corpus. Previous work had assumed that some features were immune from this problem, but we show conclusively that this is not the case. This motivates the primary goal of our work, which is the search for 'cheap' (easy to collect) alternatives. In Section 3, we introduce the Lang-8 learner corpus, which has been scraped from a website where language learners write a journal to improve their English. We show that this corpus can be used for NLD, but our results suggest that the task is much more difficult than suggested by previous work, and requires more data. In Section 4, we test two options for artificial learner corpora: doubly-translated texts from the LOCNESS corpus and *n*-gram information gleaned directly from L1 texts. In Section 5, we offer our conclusions

2.   Topic bias in the ICLE

2.1.   Quantitative Analysis

The ICLE, which in its current version contains 6085 essays from 16 different languages, is intended to reflect, among other things, the state of EFL teaching in each of the countries around the world. An obvious challenge in building a corpus like the ICLE is incorporating the work of many researchers, educators and of course learners from different countries into a coherent whole. An original list of topics was chosen by the coordinating team, but leeway was clearly given to the organizers in each country, since some of the topics were, for instance, only relevant to Europeans (e.g. the future of a united Europe). Even when the original topic list was used, there were obvious biases in the particular topics chosen, with certain topics being dominated by certain L1 backgrounds (Granger et al. 2009:6–7). This explains why many NLD researchers have avoided word features when working in the ICLE; a classifier can simply learn to distinguish L1 by distinguishing topics. However, the problem extends deeper than that: we believe that certain topics are correlated with entirely different registers, which might have an effect on features that go beyond topic words. For example,

many of the most common topics in the French subset of the corpus involve the relatively esoteric subjects of literature, religion, and politics, which might be discussed in a fairly formal register. In the Japanese corpus, however, we found a number of topics that were far more personal, for instance experience as an English learner and favorite travel destinations, which would likely be expressed in a more narrative and more colloquial manner. Arguably, these might reflect real differences in culture, but in the context of a corpus that cannot possibly reflect the full range of genres, we believe that these variations are extremely confounding for machine-learning based NLD, and they can affect a full range of feature types.

2.2.   Experiment #1: Measuring the influence of topic

In order to test whether the variation in the ICLE is having an effect by artificially boosting classification accuracy, we carried out the first in a series of experiments. Most of our experiments in this paper will use the same feature set, which is a core set of features from previous work: function words, character n-grams, and part-of-speech (POS) n-grams; we also include word n-grams, which have mostly been avoided. Here n-grams includes unigrams (single elements) and bigrams (pairs of elements). The POS is automatically tagged (Schmid 1995) Our input to the machine classifier consists of the normalized (to 1000 words) frequency of these elements in the texts. For classification, we use the SVM algorithm included in the WEKA machine learning software (Witten & Frank 2005), with default settings. We report accuracy as the total number of texts whose author's L1 was correctly identified. Another constant is our notation for statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, though in different tables the numbers which are being compared may vary.

Our first experiment uses four languages from the ICLE: French, Spanish, Chinese, and Japanese. Using the annotation included in the ICLE, we took 200 texts from each sub-corpus and divided them into groups of 100 texts based on topic; all texts of a particular topic from the same L1 appeared in the same set. Then we took the same 200 texts, and just randomly distributed them into two sets. For each of these divisions, we trained a classifier on one set, and tested on the other, and then reversed the roles (so our results reflect the classification of all 800 texts). We hypothesized that if topic is playing a major role in NLD performance, the randomized version, which has topics with are spread across the training and testing sets, will be able to take advantage of that, while the topic segmented version will not be able to.[1]

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[1] Or at least will have less opportunity . Some of the different topics have certain common meta-topics (e.g. politics) which could still be used by the classifier. We did not attempt to control for this.

Feature set	Randomized split	Topic-based split
Character *n*-grams	82.9	50.2***
POS *n*-grams	92.1	85.0***
Function words	85.2	77.1***
Word *n*-grams	96.2	82.5***
Combined	96.5	86.1***

Table 1. NLD accuracy (%) in ICLE, 4-language, randomized vs. topic-based crossvalidation

The results in Table 1 show that topic is indeed playing a major role in NLD, and the effect is not limited to words. All of the classifiers trained and testing using the topic-split version performed worse, and these results are highly significant. Character *n*-grams are by far the biggest offender; we posit that the distinct characters in words in the title are driving the high performance, and without that information character *n*-grams are simply not competitive. By contrast, the drop in word *n*-grams is fairly modest. But what is particularly troubling is the drop for POS *n*-grams and function words; these were supposed to be immune from the effects of topic, but clearly are not. Thus, we need to reconsider the validity of training and testing in the same corpus where topic variation is so confounding, and look for alternatives.

3.   A new 'cheap' corpus: The Lang-8 learner corpus

The construction of the ICLE was a major project that took several years. Though it will likely continue to expand, we doubt it will be repeated in the near future. However, it is not sufficient for our needs; as we saw in the previous section, it is biased in a way that interferes with the reliability of our results. However, a huge amount of non-native language is being produced constantly around the world, every day, and some of it is on the World Wide Web, making it accessible to us (if we can find it). The data we derived from such 'cheap' sources will almost certainly have noise, but, for data-driven approaches, it can make up for that fact by being available in almost unlimited quantities.

3.1.   A description of the Lang-8 learner corpus

The Lang-8 website[2] provides a means for language learners to practice by writing journal entries in the language they are studying, which in turn is corrected by native speakers of that language who visit the site. We extracted a large collection of journals from the site, including 154,702 entries, or 22 million words. The site is based in Ja-

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[2] http://lang-8.com

pan, and so learners of East Asian origin are disproportionately represented; however, among the entries in our corpus there are 65 different native languages included, with 14 of those languages having at least 1000 entries. Compared to the numerous variables that are recorded in manually collected learner corpora such as the ICLE, the information we have about each entry is rather minimal: other than (self-reported) native language and target language, we have a (unique) user name and the time which the entry was posted, though we use neither in the investigations reported here. There is some additional information available in the user profiles (e.g. gender), but we did not collect this information.

The ICLE contains primarily argumentative essays. The Lang-8 journal entries, by contrast, tend to be short personal narratives, though there are many exceptions: some users post their homework assignments, or ask for explicit translation or correction of a particular phrase out of the context of a coherent discourse. Though we did not carry out a rigorous analysis, the overall quality of the Lang-8 entries, i.e. the English proficiency of the users, seems to be generally much lower than the ICLE texts (which are written by university students). Moreover, the Lang-8 texts, because they are written entirely at the discretion of the user, appear to be more error-avoiding (Corder 1974); for the most part, users stay in their comfort zones, an effect which we posit is amplified by the knowledge that their text may be critiqued by native speakers. On the other hand, there are (presumably) no limits on the time or other resources that users may use to create the entries, so some entries may represent a fairly major investment, including revisions.

3.2. Experiments

3.2.1. Experiment #2: Train on one, test in the other

Armed with this new corpus, we wanted to see whether it could be used for NLD research, either by itself, or in concert with the ICLE. Our second experiment is a 7-language task (the 7 languages that are well represented in both corpora) with 200 texts per language per corpora. Since the texts in the Lang-8 corpus tend to be much shorter, our texts actually consist of multiple texts; we combined them such that the average text lengths for the two corpora were comparable. The conditions for the experiment are: single corpus classification (10-fold crossvalidation) with each of the two corpora or training on one corpus, and testing on another (that is, cross-corpus testing). The random baseline for this task is 14.2%, and our significance results reflect comparison to that baseline.

Feature set	ICLE, single corpus	ICLE, Lang-8 training	Lang-8, single corpus	Lang-8, ICLE training
Character *n*-grams	76.9***	17.8***	18.2***	15.7
POS *n*-grams	83.8***	22.1***	20.1***	16.6*
Function words	70.1***	20.1***	20.1***	15.8
Word *n*-grams	91.8***	20.8***	21.8***	17.0**
Combined	93.8***	22.9***	25.0***	16.6*

Table 2. NLD accuracy (%), ICLE and Lang-8, 7-language, crossvalidated vs. cross-corpus

Most of the results in Table 2 are poor, though most are nonetheless significantly better than chance, suggesting that some NLD is occurring. The outlier, of course, is cross-validation in the ICLE, which is extremely high compared to cross-validation in the Lang-8, though the conditions are similar. The explanation for this, again, is the biases in the ICLE that allow for easy classification by topic. Importantly, performance in the Lang-8 using the ICLE as training is extremely poor, suggesting that the patterns the classifier has learned in the ICLE do not generalize. In fact, they confound; we noticed that most Lang-8 texts are classified as Japanese, which, of the languages in the ICLE, seems to involve the most personal narratives (see Section 2.1). The other two results are better, but still lower than we would expect. Looking at the features, we note that word *n*-grams tend to do the best, though POS *n*-grams are also useful. In any case, this task appears to be more difficult than cross-validated results in the ICLE would indicate.

3.2.2. Experiment #3: The more data, the better?

One advantage of cheap data is the potential to get a lot of it. In the case of the Lang-8 corpus, the amount of data available for the European languages is actually much less than the ICLE, but the data available for two Asian languages, Japanese and Chinese, is much greater. Our next experiment tests the effect of adding more data. Does it improve the results we saw in Experiment #2? We created three Lang-8 training sets containing increasing amounts of Japanese and Chinese data, trained classifiers, and tested in the ICLE (200 texts for each language). The guessing baseline is 50%, but in Table 3, the significance testing reflects a comparison with the number in the previous column (i.e. did adding the data help?).

Feature set	200 text Lang-8	1000 text Lang-8	5000 text Lang-8
Character *n*-grams	39.5	54.3[***]	64.3[***]
POS *n*-grams	60.8	70.3[***]	73.0
Function words	58.3	64.0[*]	65.5
Word *n*-grams	64.5	67.8	81.8[***]
Combined	67.8	70.5	81.5[***]

Table 3. NLD accuracy (%), train in Lang-8, test in ICLE, 2-language task, increasing data

The result is clear: adding data makes a big difference. For all the features, there is a statistically significant increase in performance. The pattern here is interesting: POS *n*-grams and function words get a big boost when moving from 200 texts to 1000 texts, but after that the increase is negligible. Word *n*-grams, however, get little benefit from the move from 200 to 1000, but a big benefit going from 1000 to 5000. This suggests that words, despite being mostly ignored or avoided in previous work, have the best long-term potential to improve NLD accuracy. Lexical choice almost certainly plays a key role in the phenomenon of language transfer (Odlin 1989), but we need a lot of data to properly identify the lexical items that are relevant, since there are many more of them than POS and function words.

4.   Artificial Learner Corpora

Another approach to the problem of data scarcity in NLD is to side-step learner corpora altogether. This idea explicitly relies on the theory of language transfer (Odlin 1989), that the patterns in the L2 that distinguish the learners are a direct result of their L1. If this is the case, can the L1 itself be a source of information?

4.1.   Experiment #4: Training on double-translated texts

Our first approach involves leveraging an automatic machine translation system to imbue English text with the style of a foreign language by translating through that language. For this purpose, we tested two web-based translation systems, Google Translate[3] and Yahoo! Babel Fish[4]. Starting with texts from the LOCNESS corpus[5], the native English counterpart from the ICLE, we translated them into each of four languages (again, Chinese, Japanese, French, and Spanish), and then translated them back

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[3] http://translate.google.com/
[4] http://babelfish.yahoo.com/
[5] http://www.uclouvain.be/en-cecl-locness.html

into English. We used the result as a training set, with the version of the corpus translated through, for instance, Chinese, taking the place of a corpus of texts written by learners whose L1 is Chinese. One major advantage of this approach is that, since a single English corpus is used as the starting point, there is no possibility of topic bias. We test with both the ICLE and Lang-8 (200 texts for each language). The significance results are the result of a comparison with the baseline, 25%.

Feature set	ICLE, BF	ICLE, Google	Lang-8, BF	Lang-8, Google
Character n-grams	29.6**	31.6***	25.8	25.8
POS n-grams	27.0	38.0***	20.1	29.3**
Function words	29.1**	37.8***	24.6	30.9***
Word n-grams	30.5***	38.4***	24.6	28.7*
Combined	30.4***	38.8***	24.3	29.4**

Table 4. NLD accuracy (%), train with LOCNESS doubly-translated texts, test in ICLE and Lang8, 4-language task

The results in Table 4 are not impressive, but, for those involving either Google or the ICLE, they are significantly above chance. Google Translate, which is known to be a statistical translation system, seems to reflect the L1 more than Babel Fish, which is thought to be rule-based. The discrepancy between ICLE and Lang-8 suggests that ICLE, independent of the bias, may also just be an easier test set.

4.2. Experiment #5: NLD directly with L1 corpora

We briefly mention some other current work of ours that is also based on language transfer. Here, the idea is to extract information, particularly information related to lexical use, from the L1 corpus directly. We do not present the details here, but the basic idea is this: given a large corpus of some (non-English) L1, our software passes through the text, translating individual words and pairs of words into English using a bilingual lexicon, creating a database of counts. If a word or expression is commonly used in some L1, the direct English translation will have a high count. Then, if a particular word or expression appears in some non-native English text, we can look up the counts in our database, creating a ratio for each pair of languages. We sum the ratios across all the uncommon words and (two-word) expressions in the text to get a set of total ratios for the texts, and then sum across languages to get a score for each language; if a text has a high Chinese score relative to other texts, it will be classified as Chinese. Table 5 shows some preliminary results for Chinese and Japanese, with 'training' (collecting counts) in 100 million blog corpora (Burton et al. 2009).

Feature set	ICLE	Lang-8
Word *n*-grams	67.0***	61.8***

Table 5. NLD accuracy (%), L1 method, test in ICLE and Lang-8

For this method, we only use n-grams (POS features do not translate well). The performance in Table 5 is fairly good; for the ICLE, it is similar to the results when training with 1000 texts from the Lang-8 (though not as good as 5000). There are two key advantages of this method: first, L1 corpora are usually available in abundance. Second, it allows for us to build a correspondence between forms in the L2 and their source forms in the L1; this could be useful for applications such as automated error correction (Leacock et al. 2011).

5.   Conclusion

In this paper we have shown that the primary multiple-L1 learner corpus, the ICLE, has serious problems when applied to the task of native language detection; in particular, the topic biases resulting from the way the corpus was built is a confounding factor that results in crossvalidated performance that is misleading, and training that is useless. Our approach here was to look for other, cheap ways to get training data for NLD; we presented the web-scraped Lang-8 learner corpus, and showed that it is useful for the task, particularly if large quantities of data are used. We also investigated ways to do NLD that don't involve having learner corpora at all. All of these avenues are promising, and future work will include seeing how they might be combined to create a state-of-the-art system.

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