Identifying the L1 of non-native writers: the CMU-Haifa system

Chris Dyer* **Manaal Faruqui*** **Noam Ordan†** **Nathan Schneider***
Yulia Tsvetkov* **Naama Twitto†** **Shuly Wintner†**

*Language Technologies Institute
Carnegie Mellon University
Pittsburgh, PA
cdyer@cs.cmu.edu

†Department of Computer Science
University of Haifa
Haifa, Israel
shuly@cs.haifa.ac.il

Abstract

Given a dataset of English essays composed by non-native speakers, as part of the TOEFL exam, we identify with high accuracy the native language of the authors. We use standard text classification techniques, but define sophisticated classifiers that are sensitive to the specific patterns observed in the English of authors whose first language is structurally different. We describe the various features used for classification, as well as the settings of the classifier that yielded the highest accuracy.

[$^{NS}_{S}$ shouldn't we use the official bib style file instead of natbib?]

1 Introduction

The task we address in this work is identifying the native language (*L1*) of non-native English authors. More specifically, given a dataset (Blanchard et al., 2013) of short English essays, composed as part of the TOEFL exam (of English as a foreign language) by authors whose native language is one out of 11 possible languages (Arabic, Chinese, French, German, Hindi, Italian, Japanese, Korean, Spanish, Telugu, and Turkish), our task is to identify that language.

This task has a clear empirical motivation. Non-native speakers make different errors when they write English, depending on their native language (Swan and Smith, 2001); understanding the different types of errors is a prerequisite for correcting them (Leacock et al., 2010), and systems such as the one we describe here can shed interesting light on such errors. Tutoring applications can use our system to identify the native language of students and offer better-targeted advice. Forensic linguistic applications are sometimes required to determine the L1 of authors (Estival et al., 2007a,b). Additionally, we believe that the task is interesting in and of itself, providing a better understanding of non-native language. We are thus equally interested in defining *meaningful* features whose contribution to the task can be linguistically interpreted.

We address the task as a multiway text-classification task; we specify our methodology in §3. As in other author attribution tasks (Juola, 2006), the choice of features for the classifier is crucial; we discuss the features we define in §**??**. We report our results in §7 and conclude with suggestions for future research.

2 Related work

The task of L1 identification was introduced by Koppel et al. (2005a,b), who work on the International Corpus of Learner English (Granger et al., 2009), which includes texts written by students from Russia, the Czech Republic, Bulgaria, France, and Spain. The texts lengths range from 500 to 850 words. The classification method is a linear SVM, and features include 400 standard function words, 200 letter *n*-grams, 185 error types and 250 rare part-of-speech (POS) bi-grams. Ten-fold cross-validation results on this dataset are 80% accuracy.

The same experimental setup is assumed by Tsur and Rappoport (2007), who are mostly interested in testing the hypothesis that an author's choice of words in a second language is influenced by the phonology of his or her L1. They confirm this hypothesis by carefully analyzing the features used by

Koppel et al., controlling for potential biases.

Wong and Dras (2009, 2011) are also motivated by a linguistic hypothesis, namely that syntactic errors in a text are influenced by the author's L1. Wong and Dras (2009) analyze three error types statistically, and then add them as features in the same experimental setup as above (using LIBSVM with a radial kernel for classification). The error types are subject-verb disagreement, noun-number disagreement and misuse of determiners. Addition of these features does not improve on the results of Koppel et al.. Wong and Dras (2011) further extend this work by adding as features horizontal slices of parse trees, thereby capturing more syntactic structure. This improves the results significantly, yielding 78% accuracy compared with less than 65% using only lexical features.

Kochmar (2011) uses a different corpus, the Cambridge Learner Corpus, in which texts are 200-400 word long, and are authored by native speakers of five Germanic languages (German, Swiss German, Dutch, Swedish and Danish) and five Romance languages (French, Italian, Catalan, Spanish and Portuguese). Again, SVM is the classification device. Features include POS n-grams, character n-grams, phrase-structure rules (extracted from parse trees), and two measures of error rate. The classifier is evaluated on its ability to distinguish between pairs of closely-related L1s, and the results are usually excellent.

A completely different approach is offered by Brooke and Hirst (2011). Since training corpora for this task are rare, they use mainly L1 (blog) corpora. Given English word bi-grams $\langle e_1, e_2 \rangle$, they try to assess, for each L1, how likely it is that an L1 bi-gram was translated literally by the author, resulting in $\langle e_1, e_2 \rangle$. Working with four L1s (French, Spanish, Chinese, and Japanese), and evaluating on the International Corpus of Learner English, the results are lower than 50%.

Our dataset in this work is different, and consists of TOEFL essays written by speakers of eleven different L1s (Blanchard et al., 2013), distributed as part of the First Native Language Identification Shared Task (Tetreault et al., 2013). We use a plethora of features; some of them are inspired by previous work outlined above, but many are motivated by other author attribution tasks, in particular identification of *translationese*, the language of translated texts (Volansky et al., Forthcoming).

3 Methodology

Characteristics of the dataset. Development, train, test sets.

For classification we use *creg*...

Pre-processing: POS-tagging, etc.

4 Model Overview

[$^{NS}_{S}$ I think we should break this up into sections by feature group (below). Here we can talk about learning and regularization and give a high-level overview of features.]

We define a large arsenal of features, our motivation being both to improve the accuracy of classification and to be able to interpret the characteristics of the language produced by speakers of different L1s. In this section we define the features and motivate their use.[1] While some of the features were used in the works surveyed in §2, many are novel, and are inspired by the features used to identify translationese by Volansky et al. (Forthcoming). We also report the accuracy of using each feature type, in isolation, on the training set.

Character n-grams The number of character 1-, 2-, and 3-grams. 69.94%.

Frequent character n-grams Only those character n-grams that are observed more than m times in the corpus are considered. ??? [$^{N}_{T}$ this includes 1 to 4 n-grams, resulting in 74.12%]

POS n-grams All essays were tagged with the Stanford part-of-speech tagger (Toutanova et al., 2003). Features were extracted to count every POS 1-, 2-, and 3-gram in each document. 53.92%.

Document length The number of tokens in the text. 11.81%.

Pronouns The number of each pronoun. 22.81%.

Punctuation The number of each punctuation mark. 27.41%.

Passives The ratio of verbs to passive verbs. 12.26%.

Positional token frequency The choice of the first and last few words in a sentence is highly con-

[1] Whenever counts are mentioned, we use the log of the count as the feature.

strained, and may be significantly influenced by the authors L1. We use the counts (???)[Y T counts for first two and last three words before the period] of the first and last three words in each sentence as features. 53.03%.

Cohesive markers These are 40 function words (and short phrases) that have a strong discourse function in texts [N T such as 'however', 'becuase', 'in fact' etc], contributing to its cohesiveness. 25.71%. [N T Translators tend to spell out implicit utterances and render them explicitly in the target text (REFERENCE TO BLUM-KULKA); MAYBE APPEND THE LIST IN THE END?]

Cohesive verbs [N T This is a list of manually compiled verbs that serve, like 'cohesive markers' to spell out implicit utterances; they include, among others, 'indicating', 'implying' and 'containing'. Same, consider appending the list]. 22.85%.

Function words The number of occurrences of each word from a pre-defined list of 100 [N T did you use only 100? it should be 400 and the reference should be to Koppel and Ordan] [Y T we used 100. differences between 100 and >100 were insignificant] most frequent words in English (excluding punctuation). 42.47%.

Contextual function words, bigrams Pairs consisting of a function word from the list mentioned above, along with the POS tag of its adjacent word. This feature captures patterns such as verbs and the preposition or particle immediately to their right, or nouns and the determiner that precedes them. 62.79%

Contextual function words, trigrams Same as above, but counting [N T 2- or] 3-grams consisting of one or two function words (respectively) and the POS tag of the third word [N T character?] in the [N T 2- or] 3-gram. 62.32%.

Lemmas [N T these should be actually 'stems' as produced by the Stanford tagger] The number of each of the most frequent lemmas in the text. ???. 58.95%.

Prompt Conjunction of the character *n*-gram features defined above with the prompt; since the prompt contributes information on the domain, it is likely that some words (and, hence, character sequences) will occur more frequently with some prompts than with others. 65.09%.

Misspelling features ???. 37.29%.

Brown ???

Restored [Y T Counts of substitutions, deletions and insertions of predefined tags that we restored in essays edited with a spelling corrector and missing all these tags. We define three types of tags: (1) punctuation marks (same list as for punctuation feature), (2) function words (WH-words, prepositions, conjunctions, articles, auxiliary verbs, quantifiers, personal pronouns, possessive pronouns, quantified pronouns), (3) cohesion verbs (lemma, present contiguous/progressive and present simple for each verb). We first remove these tags from texts and then recover the most likely hidden tags in a sequence of words, according to an N-gram language model trained on all essays in the training corpus corrected with a spell checker and containing both words and hidden tags. This feature should capture specific words or punctuation marks that are consistently omitted (deletions), or misused (insertions, substitutions). To restore hidden tags we use hidden-ngram utility provided in SRILM toolkit[2] (ref to SRILM). 47.67%]

5 Main Features

These four feature groups form the core of our model.

5.1 POS: part-of-speech sequences

5.2 FreqChar: frequent character *n*-grams

5.3 CharPrompt: character *n*-grams paired with the prompt ID

5.4 Brown: Brown clusters

6 Additional Features

Each of these adds a small number of parameters to the model. We report the empirical improvement that each of these brings independently when added to the main features (§5). The full model combines all features.

6.1 CxtFxn: Contextual function words[NS S does this subsume pronouns?]

[N T yes]

[2] http://www.speech.sri.com/projects/srilm/manpages/hidden-ngram.1.html

Feature Group	# Params	Accuracy (%)	ℓ_2
POS	540,947	55.18	1.0
+ FreqChar	1,036,871	79.55	1.0
+ CharPrompt	2,111,175	79.82	1.0
+ Brown	5,664,461	81.09	1.0

Table 1: Dev set accuracy with MAIN feature groups, added cumulatively. The number of parameters is always a multiple of 11 (the number of classes). Only ℓ_2 regularization was used for these experiments; the penalty was tuned on the dev set as well.

Feature Group	# Params	Accuracy (%)	ℓ_2
MAIN + Position	6,153,015	81.00	1.0
MAIN + PsvRatio	5,664,472	81.00	1.0
MAIN	5,664,461	81.09	1.0
MAIN + DocLen	5,664,472	81.09	1.0
MAIN + Pron	5,664,736	81.09	1.0
MAIN + Punct	5,664,604	81.09	1.0
MAIN + Misspell	5,799,860	81.27	5.0
MAIN + Restore	5,682,589	81.36	5.0
MAIN + CxtFxn	7,669,684	81.73	1.0

Table 2: Dev set accuracy with MAIN features plus additional feature groups, added independently. ℓ_2 regularization was tuned as in table 1 (two values, 1.0 and 5.0, were tried for each configuration; more careful tuning might produce slightly better accuracy). Results are sorted by accuracy; only three groups exhibited independent improvements over the MAIN feature set.

6.2 DocLen: Document length in tokens

6.3 Misspell: Spelling correction edits

6.4 Position: [$^{NS}_{S}$?]

6.5 Pron: pronouns[$^{NS}_{S}$?]

[$^{N}_{T}$ A list of 25 pronouns in English, again, append list]

6.6 PsvRatio: Ratio of passive to active voice verbs[$^{NS}_{S}$ or is it the proportion of passive verbs?]

6.7 Punct: Count of each punctuation mark

6.8 Restore: LM-restored function words

6.9 Discarded Features

[$^{NS}_{S}$ things that didn't help in our preliminary experiments]

7 Results

8 Conclusion

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	ARA	CHI	FRE	GER	HIN	ITA	JPN	KOR	SPA	TEL	TUR	Precision (%)	Recall (%)	F_1 (%)
ARA	80	0	2	1	3	4	1	0	4	2	3	80.8	80.0	80.4
CHI	3	80	0	1	1	0	6	7	1	0	1	88.9	80.0	84.2
FRE	2	2	81	5	1	2	1	0	3	0	3	86.2	81.0	83.5
GER	1	1	1	93	0	0	0	1	1	0	2	87.7	93.0	90.3
HIN	2	0	0	1	77	1	0	1	5	9	4	74.8	77.0	75.9
ITA	2	0	3	1	1	87	1	0	3	0	2	82.1	87.0	84.5
JPN	2	1	1	2	0	1	87	5	0	0	1	78.4	87.0	82.5
KOR	1	5	2	0	1	0	9	81	1	0	0	80.2	81.0	80.6
SPA	2	0	2	0	1	8	2	1	78	1	5	77.2	78.0	77.6
TEL	0	1	0	0	18	1	2	1	1	73	3	85.9	73.0	78.9
TUR	4	0	2	2	0	2	2	4	4	0	80	76.9	80.0	78.4

Table 3: Official test set confusion matrix with the full model. [$^{\text{NS}}_{\text{S}}$ which direction is predicted vs. gold?] Accuracy is 81.5%.

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