Classifier Stacking for Native Language Identification

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Abstract
This paper reports our contribution (team WLZ) to the NLI Shared Task 2017 (essay track). We first extract lexical and syntactic features from the essays, perform feature weighting and selection, and train linear support vector machine (SVM) classifiers each on an individual feature type. The output of base classifiers, as probabilities for each class, are then fed into a multilayer perceptron to predict the native language of the author. We also report the performance of each feature type, as well as the best features of a type. Our system achieves an accuracy of 86.55%, which is among the best performing systems of this shared task.

1 Introduction
Native language identification (NLI) is the task of determining an author’s native language (L1) based on their writings in a second language (L2). NLI works under the assumption that an author’s L1 will dispose them towards particular language production patterns in their L2, as influenced by their native language. This relates to cross-linguistic influence (CLI), a key topic in the field of second language acquisition (SLA) that analyzes transfer effects from the L1 on later learned languages (Malmasi, 2016). The identification of L1-specific features has been used to study language transfer effects in second-language acquisition (Malmasi and Dras, 2014), which is useful for developing pedagogical material, teaching methods, L1-specific instructions and generating learner feedback that is tailored to their native language.

The first NLI shared task was held in 2013 (Tetreault et al., 2013), and the winner team reported an accuracy of 83.6% on the test data using an SVM classifier with over 400,000 unique features consisting of lexical and POS n-grams occurring in at least two texts in the training set (Jarvis et al., 2013). In addition to n-gram features, other researchers have also explored syntactic features (Bykh and Meurers, 2014) and the use of string kernels (Ionescu et al., 2014).

All NLI shared tasks to date have been based on L2 English data, but NLI research has been extended to at least six other non-English languages (Malmasi and Dras, 2015). In addition to using the written responses, a recent trend has been the use of speech transcripts and audio features for dialect identification (Malmasi et al., 2016). The combination of transcripts and acoustic features has also provided good results for dialect identification (Zampieri et al., 2017). Following this trend, the 2016 Computational Paralinguistics Challenge (Schuller et al., 2016) also included an NLI task based on the spoken response. The NLI Shared Task 2017 attempts to combine these approaches by including a written response (essay) and a spoken response (speech transcript and i-vector acoustic features) for each subject. The task also allows for the fusion of all features.

Ensemble methods using multiple classifiers have proven to be one of the most successful approaches for the task of NLI (Malmasi and Dras, 2017), and researchers have reported better results using stacking than a single classifier in other text classification tasks (e.g., Liu et al., 2016). In this work we present a stacking model using lexical and syntactic features for NLI Shared Task 2017 (Malmasi et al., 2017), report the performance of different feature types, and show the best features in each type. The features we use in the final model include character/word/stem n-grams, function word n-grams, and dependency parses.
2 Data
The data set we use for NLI Shared Task 2017 (see details in Malmasi et al., 2017) includes English essays written by test takers who participated in a standardized assessment of English proficiency for academic purposes. The 11 native languages of the test takers are: Arabic (ARA), Chinese (CHI), French (FRE), German (GER), Hindi (HIN), Italian (ITA), Japanese (JPN), Korean (KOR), Spanish (SPA), Telugu (TEL), and Turkish (TUR). There are 11,000 essays (1,000 per L1) in the training partition (Train), 1,100 (100 per L1) in the development partition (Dev), and 1,100 (100 per L1) in the test partition (Test). All essays are available in both original and tokenized texts.

3 Methods
3.1 Features
We use tf-idf weighting for all the features in this work, since we observe better results than other feature representations, namely binary representation and frequency-based representation. For most of the feature types, we also select $k$-best features with chi-square metric instead of using all of them. Previous research has reported feature selection could improve the classification accuracy (Liu et al., 2014), and we notice the same trend for this task. In preliminary experiments feature selection increases the accuracy by around 1-3% for each feature type. The $k$ value for each feature type varies with regard to the total number of features, and we choose the selected number of features based on their performance on the Dev set (trained on Train set). Both tf-idf weighting and feature selection are realized with Scikit-Learn (Pedregosa et al., 2011).

Character n-grams We extract character 3-7 grams from the tokenized text, and each is represented as a feature type (denoted by Char3-7). We also experiment with character 8-9 grams but do not include them in the final model, since adding them does not improve the accuracy.

Word n-grams We extract word uni-, bi-, and tri-grams from the tokenized text, and each is represented as a feature type (denoted by Word1-3).

Lemma n-grams We use the WordNet Lemmatizer in NLTK (Bird, 2006) to lemmatize the tokenized essays, and then extract lemma uni-, bi-, and tri-grams as feature types (denoted by Lemma1-3). However, we do not include these features in the final model, since adding them does not improve the accuracy.

Stem n-grams We first stem the tokenized text with Porter stemmer using NLTK, and then extract stem uni-, bi-, and tri-grams as feature types (denoted by Stem1-3).

POS n-grams We use the Stanford POS tagger (Toutanova et al., 2003) to tag the tokenized essays, and then extract POS uni-, bi-, and tri-grams as feature types (denoted by POS1-3). However, we do not include these features in the final model, since adding them does not improve the accuracy.

Function word n-grams We use the Stanford POS tagger to tag the tokenized essays first, and then extract the function words by their POS tags (which are tagged as auxiliary verbs, conjunctions, determiners, pronouns, etc.). Function word uni-, bi-, and tri-grams are used as features (denoted by FW1-3).

Dependency parses We use the Stanford dependency parser (Klein and Manning, 2003) to extract the dependencies from the tokenized essays. Three types of dependencies are included in the experiments (taking “I agree” as an example): original dependency (Dep0), e.g., (agree, nsubj, I); dependency where one of the word is replaced by its POS tag (Dep1), e.g., (VBP, nsubj, I) and (agree, nsubj, PRP); dependency where both of the words are replaced by their POS tags (Dep2), e.g., (VBP, nsubj, PRP). We include the POS-replaced dependencies, since we believe they would generalize better, as noted by Malmasi and Dras (2017).

Word embeddings We use the Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors) in GloVe (global vectors for word representation) (Pennington et al., 2014) to produce feature vectors for each essay, with the help of Gensim (Řehůřek and Sojka, 2010). For all the words in an essay, we average their word vectors if they occur in the GloVe vocabulary as well. We observe that word vectors with larger dimension perform better than those with lower dimension when experimenting with different dimensions (e.g., 50d, 100d, 200d, 300d). However, we do not include the word embedding features (denoted by WV300) in the final model, since adding them does not improve the accuracy.
| Feature type | Total # | Selected # | CV   | Dev   | Test   |
|-------------|---------|------------|------|-------|--------|
| Char3       | 11,320  | 10,000     | 0.7327 | 0.7447 | 0.7555 |
| Char4       | 51,072  | 30,000     | 0.7944 | 0.7827 | 0.8145 |
| Char5       | 145,575 | 30,000     | 0.8158 | 0.8045 | 0.8264 |
| Char6       | 334,117 | 30,000     | 0.8260 | 0.8000 | 0.8309 |
| Char7       | 631,139 | 50,000     | 0.8386 | 0.8018 | 0.8336 |
| Word1       | 25,950  | 20,000     | 0.7699 | 0.7627 | 0.8136 |
| Word2       | 205,625 | 50,000     | 0.8417 | 0.7809 | 0.8245 |
| Word3       | 384,184 | 50,000     | 0.8227 | 0.7082 | 0.7218 |
| Stem1       | 145,575 | 10,000     | 0.7572 | 0.7618 | 0.7827 |
| Stem2       | 334,117 | 30,000     | 0.8276 | 0.7791 | 0.8118 |
| Stem3       | 631,139 | 30,000     | 0.7982 | 0.6964 | 0.7127 |
| FW1         | 511     | all        | 0.4199 | 0.4309 | 0.4227 |
| FW2         | 12,385  | all        | 0.4623 | 0.4764 | 0.4900 |
| FW3         | 104,770 | all        | 0.4174 | 0.4300 | 0.4464 |
| Dep0        | 253,719 | 30,000     | 0.7868 | 0.6718 | 0.7473 |
| Dep1        | 256,271 | 30,000     | 0.7996 | 0.7336 | 0.7709 |
| Dep2        | 4,426   | 4,000      | 0.4598 | 0.4645 | 0.4745 |
| Lemma1      | 22,541  | 20,000     | 0.7614 | 0.7627 | –      |
| Lemma2      | 181,533 | 50,000     | 0.8389 | 0.7891 | –      |
| Lemma3      | 355,414 | 50,000     | 0.8242 | 0.7082 | –      |
| POS1        | 44      | all        | 0.3516 | 0.3800 | –      |
| POS2        | 12,385  | all        | 0.5297 | 0.5173 | –      |
| POS3        | 18,961  | 15,000     | 0.5741 | 0.5710 | –      |
| WV300       | 300     | 300        | 0.5645 | 0.5673 | –      |

Table 1: Total number of features, selected number of features, and accuracy of each feature type. CV: 10-fold cross validation on Train; Dev: trained on Train, tested on Dev; Test: trained on Train and Dev, tested on Test. Best performance of a feature group on Test is in bold.

3.2 Classifiers

We use **linear SVM** (implemented by Scikit-Learn) as the base classifier for the feature types mentioned above. We set C=0.8 for Char3, Word1, Stem1, FW1-3, and Dep2, and use default settings for other parameters. Experiments on other feature types use the default setting: C=1.0, L2 penalty, squared hinge loss, etc. For each feature type, we run 10-fold cross validation on Train and test on Dev to decide the number of selected features we would like to use for the final system.

To combine the output of probabilities from base classifiers and predict the final label, one method is to concatenate all the probabilities and feed into a classifier to generate the final prediction. We examine the performance of **multilayer perceptron** (MLP), linear SVM, Linear Discriminant Analysis (LDA), and MLP performs the best. We try different hidden layer sizes, and finally use one hidden layer of 100 perceptrons. Since MLP produces different results in every run, our final results using MLP contains the average results of 10 runs to reduce the variance.

We also try combining the probabilities mathematically: 1) summing up the probabilities from all feature types and taking the maximum as final prediction (denoted by SumProbs); 2) summing up the logarithmized probabilities from all feature types and taking the maximum as final prediction (denoted by LogSumProbs).

We run cross validation on Train and Dev to decide which feature types to include in the final model.

4 Results

4.1 Results by feature type

We report the performance of each feature type in Table 1. The upper part contains the 17 features we use in the final model, and the lower part contains some features we would like to explore but do not include in the final submissions.
We can see that the total number of features is very large for some feature types, which makes feature selection necessary. However, we choose the number of features by their performance on Dev and cross validation on Train, so there is no guarantee that we have the optimal number of selected features.

The features that perform comparatively well on Test set are: Char7, Word2, Stem2, FW2, and Dep1. We believe that bigrams perform better than unigrams or trigrams in general, because they consider context more than unigrams and generalize better than trigrams.

We also show the top features for each feature type ranked by Chi-square in Table 4, in the hope that it would be helpful for researchers interested in SLA or at least provide some insights to the readers. We notice that among the word n-grams are some country related words such as “italy” and “in japan”, as well as some common expressions such as “in order to” and “more and more”.

4.2 Final results

The Word Unigram baseline in Table 2 is achieved by using normalized frequency of all the word unigrams (which occurred at least three times in the essays) as features, and linear SVM as the classifier.

We try different methods of combining the output of probabilities by base classifiers and report their performance in Table 2. MLP and linear SVM are the best combiners among our experiments (other classifiers include random forest, LDA, logistic regression). When not using a classifier, summing up the logarithmized probabilities achieves better results than summing up the probabilities directly. The detailed evaluation of our best performing system is shown in Table 3, and the confusion matrix is shown in Figure 1.

From the confusion matrix we observe a few quite distinctive language groups: CHI, JPN, and KOR; HIN and TEL; FRE, ITA, and SPA. We suppose the confusion between languages results more from cultural than linguistic reasons. For instance, HIN and TEL are mutually misclassified in a lot of cases, while HIN belongs to Indo-European language family and TEL belongs to Dravidian. Similarly, CHI, JPN, and KOR come from three different language families, but they are in a cluster where one is often misclassified as another.

| System               | F1 (macro) | Accuracy |
|----------------------|------------|----------|
| Random Baseline      | 0.0909     | 0.0909   |
| Word Unigram         | 0.7104     | 0.7109   |
| MLP                  | 0.8654     | 0.8655   |
| LinearSVM            | 0.8593     | 0.8591   |
| LogSumProbs          | 0.8564     | 0.8565   |
| SumProbs             | 0.8554     | 0.8555   |
| LDA                  | 0.8446     | 0.8445   |

Table 2: Final results using different combining methods. Trained on Train and Dev, tested on Test.

| System | Precision | Recall | F1  |
|--------|-----------|--------|-----|
| ARA    | 0.8673    | 0.8500 | 0.8586 |
| CHI    | 0.9388    | 0.9200 | 0.9293 |
| FRE    | 0.8600    | 0.8600 | 0.8600 |
| GER    | 0.9406    | 0.9500 | **0.9453** |
| HIN    | 0.7843    | 0.8000 | 0.7921 |
| ITA    | 0.8878    | 0.8700 | 0.8788 |
| JPN    | 0.8679    | 0.9200 | 0.8932 |
| KOR    | 0.8632    | 0.8200 | 0.8410 |
| SPA    | 0.8173    | 0.8500 | 0.8333 |
| TEL    | 0.8265    | 0.8100 | 0.8182 |
| TUR    | 0.8700    | 0.8700 | 0.8700 |
| **avg / total**     | **0.8658**| **0.8655**| **0.8654** |

Table 3: Detailed evaluation of our best performing system. Trained on Train and Dev, tested on Test. Best and worst F1 in bold and italics.

5 Discussion and future work

We explore the performance of different feature types for NLI in this work. Among the features types we examine, character/word/lemma/stem n-grams have the best individual performance. Dependency parses are also informative with respect to the native language of the author. POS n-grams might be too general for this task, achieving around 50% accuracy alone. Word embeddings are good indicators for text classification tasks such as sentiment analysis, which relies heavily on the semantics of the content. NLI is not only about the semantics of the text but also involves writing style (e.g., the use of expressions and sentence structure). We suppose this justifies the performance of using word embeddings as features.

When we combine the output of base classifiers using different feature types to predict the final label, we have to decide which feature types to include. It is not practical to try all the combinations of features, so we start with the feature types
Figure 1: Confusion matrix of our best performing model.

We notice MLP improves the system performance over linear SVM as a combiner. For an individual feature type, MLP also performs better than linear SVM in most cases; however, we choose linear SVM as the base classifier, since it has better balance between speed and accuracy. MLP is roughly ten times slower than linear SVM when we run the experiments. This points us to the use of neural networks, since MLP is one of the simplest neural architecture. We would like to explore more about neural networks for NLI in future.

Another direction of future work may be towards a different architecture of combining various feature types. Ensemble methods have been studied quite a lot in text classification tasks; however, building an ensemble classifier is hardly an end-to-end task. We would like to explore how we can make the system smarter and learn by itself with less human input.

Finally, we hope the work in NLI would be of interest to the researchers from SLA/ESL. We hope the work we have done for NLI could be potentially useful for language teachers, and we would like to collaborate with them if they need anything from the view of computational linguistics.
### Table 4: Top features ranked by Chi-square on Train and Dev (separated by “;”).

| Feature Type | Top Features Selected by Chi-square |
|--------------|------------------------------------|
| Char3 | b, vel; ink; nj; alo; pan; t; ooup; oft; u; w; oee; k; yee; fue; u; nk; m; a; be; i; u; x; &; ...; t; gst; yme; tit; t; wev; bo; gu; eym; ap; ap; ap; gu; gu; tid; ow; rav; ...; ja; urk; ko; ou; ko; jap |
| Char4 | vel; kov; gu; gste; ngst; hem; fent; ofer; bbl; oeww; wvve; llde; nk t; ymec; bo; ho; i; tl; oyme; ur; gu; g; pane; gu; joym; rky; urke; gu; guild; t; rau; deed; avel; trav; ita; nde; in; tour; in; n k; turk; pan; at; n j; yu; orea; kore; kor; jape; apan; jap |
| Char5 | i th; n; ita; avel; rean; ced; oymen; howe; our g; a th; orea; r gu; urk; gu; urke; turkey; joymen; gu; guild; t; n j; panes; pan; am; pan; ave; nwe; avr; deed; deel; ind; ndeed; tour; tour; ind; turk; in; ko; inde; aot; aot; orea; in; ja; you; n jap; apan; kore; korea; jap; japan |
| Char6 | a tour; ravel; ced; orean; howe; oymen; howe; our g; a th; orea; t; g; panes; japan; panes; anes; apan; panes; travel; travel; instead; ined; in; ko; indee; tur; tour; a tour; in; k; kor; inde; aot; aot; orea; in; ja; you; n jap; apan; kore; korea; jap; japan |
| Word1 | u; jack; developble; imact; miun; rublic; exmaple; prepation; trip; m; youth; group; &; think; the; your; varous; france; dont; ...; a; you;ngsters; he; germany; hence; his; italy; towards; traveling; particular; italian; often; however; ther; travel; i; korean; guide; enjoyment; turkey; ; ...; japan; indeeed; tour; ; aot; korea; you; japan |
| Word2 | and; bename; that; you; jack; of; the; youth; it; he; by; younger; generation; the; above; they; when; compared; in; a; particular; group; tour; you; are; first; two; reasons; a; group; particular; subject; korea; in; germany; second; now; a; we; ; second; japan; as; compared; and; ...; that; in; fact; i conclude; in; italy; as; in; france; in; turkey; a; days; however; i think; a; tour; i; however; think; that; korea; tour; guide; japan; indeeed; in; korea; ; indeeed; of; aot; aot; orea; in; jap; korea; japan |
| Word3 | a lot; have; alot; of; all; conclude; i; young; people; master; of; none; i; think; tour; guide; enjoy; a; lot; they; can; in; japan; usage; of; cars; of; all; trades; i; think; the; younger; generation; conclude; i; the; on; the; each; and; every; the; possibility; to; i; feel; that; a; group; led; therefore; however; i; reasons; i; the; one; hand; group led by; to; conclude; in; japan; for; this; reason; he; i; that; i conclude; that; in; korea; jack; of; all; led; by; when; compared; to; first; in; a; group; by; tour; are; two; reasons; in; fact; second; in; japan; as; compared; to; a; tour; guide; now; a; days; in; korea ... i think; that; indeeed |
| Stem1 | atleast; an; that; istanbul; interest; taiwan; india; commun; fuel; tokyo; trip; group; imact; possibl; jack; milan; think; toward; advertiss; differ; the; exampl; youth; dont; various; your; he; franc; he; henc; germani; itali; rublic; youngster; ofter; ther; howe; ital; korean; guide; turkey; ; travel; japanes; tour; indee; aot; korea; you; japan |
| Stem2 | all; trade; when; you; with; have; alot; feel; that; you; will; the; italian; usage; of; old; age; each; and; one; hand; in; india; people; that; master; of; group; you; have; mode; of; you; tour; led; by; to; conclude; that; and; henc; every; thing; that; you; when; compare; possibl; to; the; youth; in; group; jack; of; younger; gener; the; abol; led; by; enjoy; lot; the; subject; particular; subject; you; are; group; tour; in; germani; by; tour; two; reason; as; compare; in; fact; now; day; in; ital; where; as; in; franc; in; turkey; think; that; tour; guid; in; korea; aot; of; in; japan |
| Stem3 | the; new; thing; allot; of; thing; the; statement; and; that; for; in; olden; day; youth; of; today; are; my; follow; in order to; the; youth; of; in; today; world; would; say; that; for; these; reason; for; example; consid; the; older; people; day; by; day; in; the; way; for; new; thing; mode; of; transport; when; you; are; think; that; final; conclude; that; the; usage; of; accord; to; me; my; mind; all; the; subject; travel; in; group; the; young; people; more; and; more; you; have; think; that; in; new; have; allot; of; master; no; use; of; car; in; group; led; each; and; every; the; possibl; to; on; the; one; for; all; trade; the; younger; gener; the; one; hand; group led; by; for; this; reason; all; jack; of; all; when; compare; to; led; by; tour; by; tour; guid; are; two; reason; as; compare to |
| PW1 | when; whether; to; about; by; some; amongst; it; can; into; every; than; there; atleast; must; three; across; or; you; upon; she; till; because; behind; with; could; of; though; my; would; whereas; might; they; their; this; him; that; olden; any; the; ; its; an; may; which; your; he; his; towards; you |
| Deep1 | that; why; the; he; all; the; there; three; you; in; and; he; some; might; one; should; to; you; the; may; the; behind; any; one; that; that; this; in; you; the; because; you; his; and; that; you; of; which; he; it; to; you; and; they; can; what; you; and; towards; the; which; he; can; and; you; he; will; towards; the; by; every; one; in; by; in; olden; there; two; he; may; we; can; in; his; them; if; you; can; the; you; you; will; the; of; when; you; where; as; that; you; to |
| Deep2 | some; might; that; there; three; as; you; to; and; as; with; towards; the; their; all; but; of; the; an; you; to; in; the; twenty; in; twenty; than; there; two; the; you; to; the; olden; some; might; with; to; would; that; to; you; to; if; you; to; n; in; this; but; on; the; we; can; the; the; where; as; above; we; can; their; towards; their; of; for; that; with; these; with; the; these; may; when; you; you; all; as; before; and; for; this; the; that; you; to; where; the; two; for; in; all; in; all; as; with; the; two; for; this; can; that; as; would; in; that; of; to; by; of; the; the; that; you; on; the; each; and every |
| Deep3 | compared; around; ming; days; get; this; mind; deep; imp; enment; could; possibility; det; life; thing; det; all; every; subjects; det; the; taiwan; case; in; each; and; usage; mod; cars; self; mod; enjoy; job; lot; hand; num; one; product; det; a; subject; det; the; knowledge; det; take; job; examp; group; ac; led; conclude; mark; jk; india; case; in; people; det; life; generation; det; feel; assyj; det; generation; mod; younger; have; sbu; you; det; a; prepation; det; a; youth; det; the; led; mod; guide; reasons; num; two; tour; compound; group; group; subject; mod; particular; case; in; subject; det; the; guide; by; days; in; jk; det; the; jk; case; in; fact; case; in; italy; case; in; france; case; in; turkey; case; in; conclude; sbu; poss; his; guide; det; think; a; group; compound; tour; korea; case; in; japan; case; in |
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