Grammatical Accents: Using Machine Learning to Quantify Language Transfer

Tiwalayo Eisape[1], William Merrill[2], Sven Dietz[1], Joshua K. Hartshorne[1]
[1]Department of Psychology Boston College, [2]Department of Linguistics Yale University

Language learning lab

Motivation

Goal :
To use machine learning to establish a broad-based method to empirically study the effects of first language syntax on second language (L1->L2 transfer).

Q_1: Does NLI work in languages other than english [cf. 1]?

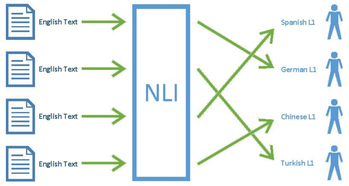
Q_{2a}: What grammatical features can we train on successfully? Which are the most informative?

Q_{2b}: Which are the most accurate* classifiers

Q_3: Can machine learning algorithms learn L1->L2 patterns that generalize across L2s?

Q_4: Are only certain parts of input (i.e language) informative? Which ones? [7]

Native-Language Identification (NLI):
The process of determining an author's native language (L1) based only on their writings in a second language (L2)



(Malmasi and Dras 2017)

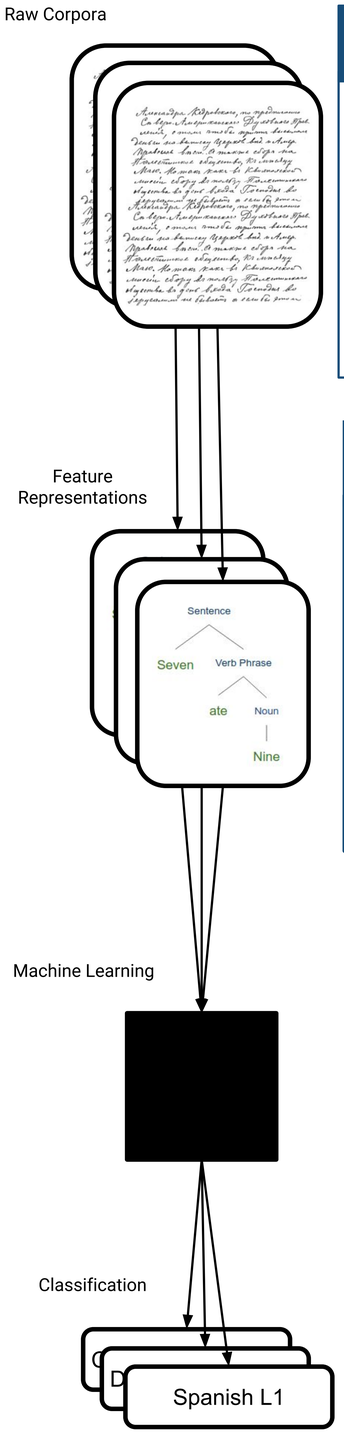
Method:
Compare the results of a variety of state-of-the-art machine learning techniques on NLI in two languages: English and Spanish.

Background

Native-language identification has been proven possible when a wide set of features is applied to the task [1]. Further more, languages besides english have been widely ignored (Q_1). As a first step, we broaden our language set to include Spanish while simultaneously restricting our feature set to exclusively syntactic features as inspired by [4].

- [3] POS n-grams <= 4-grams, dependency labels.
- [4] POS n-grams <= 4-grams. Used SVMs and shallow neural networks, achieving accuracy > 50%.
- [5] POS n-grams <= tri-grams. Used SVMs to achieve accuracy > 50%

*Accuracy was measured as a weighted average of the F1 scores of each class where F1 = 2 • (Recall • Precision) / (Recall + Precision)



Corpora

Q_1

We perform NLI on datasets in two languages: English (TOEFL) and Spanish (CAES)

TOEFL

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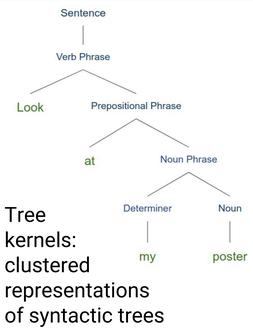
Spanish
Hindi Italian Korean Telugu
Turkish German Japanese
Arabic Chinese French
Russian Portuguese
English

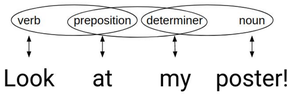
Features

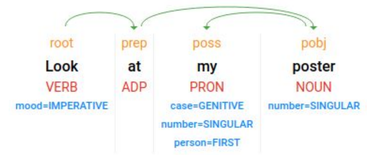


Tree kernels: clustered representations of syntactic trees

Q_{2a} Features used include labeled and unlabeled tree kernels as well as part of speech and dependency tags (TF-IDF weighting [4] was used to emphasize infrequency). Tags were generated using SyntaxNet [8].

Part of speech tags
n-grams up to
and including tri-grams





Dependency parsed representations of sentences

Models / Results

	POS	Labels	POS + Labels	
CAES	52.06	50.08	52.7	FF
	61.93	53.93	55.95	SVM
TOEFL	28.25	29.25	37.78	FF
	45.72	43.68	51.47	SVM

Support Vector Machines (SVM) and Feed Forward Neural Networks (FF) are fed clustered features.

Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) were fed features serially using padding to account for the variable length of essays

$Q_{2a} + Q_{2b}$

	POS			Labels			
	50	100	150	50	100	150	
CAES	46.35	48.6	50.25	40.38	49.5	41.28	CNN
	44.4	51.7	43.1	42.4	44.51	42.68	RNN
TOEFL	18.65	21.29	25.69	19.69	25.33	23.47	CNN
	14.43	18.27	22.9	16.2	20.2	21.82	RNN

chance for CAES = 16.67%, chance for TOEFL = 9.09%

TOEFL 52.6%

Q_3

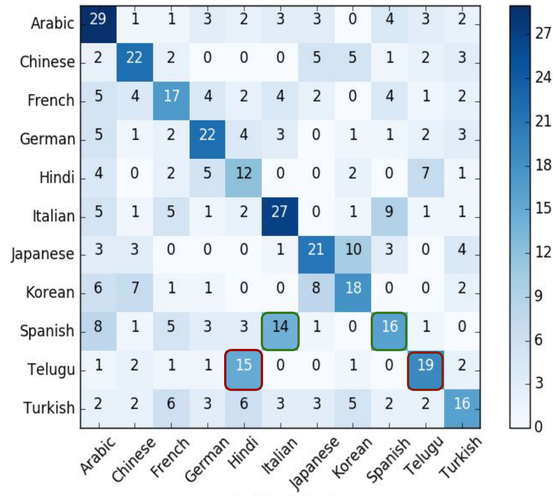
Cross-validating across languages shows some aspects of transfer generalize beyond individual L2s

Cross-validation performed on intersection of languages using FF, chance = 33.33%

	Labeled Tree Kernels	Unlabeled Tree Kernels
CAES	25.5	8.54
TOEFL	42.98	54.76

Labeled and unlabeled tree kernels [6] represent syntactic trees both by structure alone and by structure coupled with dependency labels

Insights



Insights:
1. Spanish and Italian - same language family: Italo-Western Romance
2. Hindi and Telugu - high proximity and language sharing

Conclusions / Future Directions

By achieving state of the art accuracy, using strictly syntactic features, we show machine learning can pick up on generalizable, grammatical idiosyncrasies associated with (L1 ->L2) language transfer.

Next Steps:
1. Expand features to further encapsulate syntax "Super Tagging" [2]
2. Open up the black box.
   Q_4 Reverse engineer our learning algorithms for interpretation

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