Reconstructing Native Language Typology from Foreign Language Usage

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Abstract

Linguists and psychologists have long been studying cross-linguistic transfer, the influence of native language properties on linguistic performance in a foreign language. In this work we provide empirical evidence for this process in the form of a strong correlation between language similarities derived from structural features in English as Second Language (ESL) texts and equivalent similarities obtained from the typological features of the native languages. We leverage this finding to recover native language typological similarity structure directly from ESL text, and perform prediction of typological features in an unsupervised fashion with respect to the target languages. Our method achieves 72.2% accuracy on the typology prediction task, a result that is highly competitive with equivalent methods that rely on typological resources.

1 Introduction

Cross-linguistic transfer can be broadly described as the application of linguistic structure of a speaker's native language in the context of a new, foreign language. Transfer effects may be expressed on various levels of linguistic performance, including pronunciation, word order, lexical borrowing and others (Jarvis and Pavlenko, 2007). Such traces are prevalent in non-native English, and in some cases are even celebrated in anecdotal hybrid dialect names such as "Frenglish" and "Denglish".

Although cross-linguistic transfer was extensively studied in Psychology, Second Language Acquisition (SLA) and Linguistics, the conditions under which it occurs, its linguistic characteristics as well as its scope remain largely under debate (Jarvis and Pavlenko, 2007; Gass and Selinker, 1992; Odlin, 1989).

In NLP, the topic of linguistic transfer was mainly addressed in relation to the Native Language Identification (NLI) task, which requires to predict the native language of an ESL text's author. The overall high performance on this classification task is considered to be a central piece of evidence for the existence of cross-linguistic transfer (Jarvis and Crossley, 2012). While the success on the NLI task confirms the ability to extract native language signal from second language text, it offers little insight into the linguistic mechanisms that play a role in this process.

In this work, we examine the hypothesis that cross-linguistic structure transfer is governed by the *typological properties of the native language*. We provide empirical evidence for this hypothesis by showing that language similarities derived from structural patterns of ESL usage are strongly correlated with similarities obtained directly from the typological features of the native languages.

This correlation has broad implications on the ability to perform inference from native language structure to second language performance and vice versa. In particular, it paves the way for a novel and powerful framework for *comparing native languages through second language performance*. This framework overcomes many of the inherent difficulties of direct comparison between languages, and the lack of sufficient typological documentation for the vast majority of the world's languages.

Further on, we utilize this transfer enabled framework for the task of reconstructing typological features. Automated prediction of language typology is extremely valuable for both linguistic studies and NLP applications which rely on such information (Naseem et al., 2012; Täckström et al., 2013). Furthermore, this task provides an objective external testbed for the quality of our native language similarity estimates derived from ESL texts.

Treating native language similarities obtained from ESL as an approximation for typological similarities, we use them to predict typological features without relying on typological annotation for the target languages. Our ESL based method yields 71.4% – 72.2% accuracy on the typology reconstruction task, as compared to 69.1% – 74.2% achieved by typology based methods which depend on pre-existing typological resources for the target languages.

To summarize, this paper offers two main contributions. First, we provide an empirical result that validates the systematic existence of linguistic transfer, tying the typological characteristics of the native language with the structural patterns of foreign language usage. Secondly, we show that ESL based similarities can be directly used for prediction of native language typology. As opposed to previous approaches, our method achieves strong results without access to any a-priori knowledge about the target language typology.

The remainder of the paper is structured as follows. Section 2 surveys the literature and positions our study in relation to previous research on cross-linguistic transfer and language typology. Section 3 describes the ESL corpus and the database of typological features. In section 4, we delineate our method for deriving native language similarities and hierarchical similarity trees from structural features in ESL. In section 5 we use typological features to construct another set of language similarity estimates and trees, which serve as a benchmark for the typological validity of the ESL based similarities. Section 6 provides a correlation analysis between the ESL based and typology based similarities. Finally, in section 7 we report our results on typology reconstruction, a task that also provides an evaluation framework for the similarity structures derived in sections 4 and 5.

2 Related Work

Our work integrates two areas of research, cross-linguistic transfer and linguistic typology.

2.1 Cross-linguistic Transfer

The study of cross-linguistic transfer has thus far evolved in two complementary strands, the linguistic *comparative* approach, and the computational *detection* based approach. While the comparative approach focuses on case study based qualitative analysis of native language influence on second language performance, the detection based approach revolves mainly around the NLI task.

Following the work of Koppel et al. (2005), NLI has been gaining increasing interest in NLP, culminating in a recent shared task with 29 participating systems (Tetreault et al., 2013). Much of the NLI efforts thus far have been focused on exploring various feature sets for optimizing classification performance. While many of these features are linguistically motivated, some of the discriminative power of these approaches stems from cultural and domain artifacts. For example, our preliminary experiments with a typical NLI feature set, show that the strongest features for predicting Chinese are strings such as *China* and *in China*. Similar features dominate the weights of other languages as well. Such content features boost classification performance, but are hardly relevant for modeling linguistic phenomena, thus weakening the argument that NLI classification performance is indicative of cross-linguistic transfer.

Our work incorporates an NLI component, but departs from the performance optimization orientation towards leveraging computational analysis for better understanding of the relations between native language typology and ESL usage. In particular, our choice of NLI features is driven by their relevance to linguistic typology rather than their contribution to classification performance. In this sense, our work aims to take a first step towards closing the gap between the detection and comparative approaches to cross-linguistic transfer.

2.2 Language Typology

The second area of research, language typology, deals with the documentation and comparative study of language structures (Song, 2011). Much of the descriptive work in the field is summarized in the World Atlas of Language Structures (WALS)[1] (Dryer and Haspelmath, 2013) in the form of structural features. We use the WALS features as our source of typological information.

Several previous studies have used WALS features for hierarchical clustering of languages and typological feature prediction. Most notably, Teh et al. (2007) and subsequently Daumé III (2009)

[1] http://wals.info/

predicted typological features from language trees constructed with a Bayesian hierarchical clustering model. In Georgi et al. (2010) additional clustering approaches were compared using the same features and evaluation method. In addition to the feature prediction task, these studies also evaluated their clustering results by comparing them to genetic language clusters.

Our approach differs from this line of work in several aspects. First, similarly to our WALS based baselines, the clustering methods presented in these studies are affected by the sparsity of available typological data. Furthermore, these methods rely on existing typological documentation for the target languages. Both issues are obviated in our English based framework which does not depend on any typological information to construct the native language similarity structures, and does not require any knowledge about the target languages except from the ESL essays of a sample of their speakers. Finally, we do not compare our clustering results to genetic groupings, as to our knowledge, there is no firm theoretical ground for expecting typologically based clustering to reproduce language phylogenies. The empirical results in Georgi et al. (2010), which show that typology based clustering differs substantially from genetic groupings, support this assumption.

3 Datasets

3.1 Cambridge FCE

We use the Cambridge First Certificate in English (FCE) dataset (Yannakoudakis et al., 2011) as our source of ESL data. This corpus is a subset of the Cambridge Learner Corpus (CLC)[2]. It contains English essays written by upper-intermediate level learners of English for the FCE examination.

The essay authors represent 16 native languages. We discarded Dutch and Swedish speakers due to the small number of documents available for these languages (16 documents in total). The remaining documents are associated with the following 14 native languages: Catalan, Chinese, French, German, Greek, Italian, Japanese, Korean, Polish, Portuguese, Russian, Spanish, Thai and Turkish. Overall, our corpus comprises 1228 documents, corresponding to an average of 87.7 documents per native language.

[2] http://www.cambridge.org/gb/elt/catalogue/subject/custom/item3646603

3.2 World Atlas of Language Structures

We collect typological information for the FCE native languages from WALS. Currently, the database contains information about 2,679 of the world's 7,105 documented living languages (Lewis, 2014). The typological feature list has 188 features, 175 of which are present in our dataset. The features are associated with 9 linguistic categories: Phonology, Morphology, Nominal Categories, Nominal Syntax, Verbal Categories, Word Order, Simple Clauses, Complex Sentences and Lexicon. Table 1 presents several examples for WALS features and their range of values.

One of the challenging characteristics of WALS is its low coverage, stemming from lack of available linguistic documentation. It was previously estimated that about 84% of the language-feature pairs in WALS are unknown (Daumé III, 2009; Georgi et al., 2010). Even well studied languages, like the ones used in our work, are lacking values for many features. For example, only 32 of the WALS features have known values for all the 14 languages of the FCE corpus. Despite the prevalence of this issue, it is important to bear in mind that some features do not apply to all languages by definition. For instance, feature 81B *Languages with two Dominant Orders of Subject, Object, and Verb* is relevant only to 189 languages (and has documented values for 67 of them).

We perform basic preprocessing, discarding 5 features that have values for only one language. Further on, we omit 19 features belonging to the category Phonology as comparable phonological features are challenging to extract from the ESL textual data. After this filtering, we remain with 151 features, 114.1 features with a known value per language, 10.6 languages with a known value per feature and 2.5 distinct values per feature.

Following previous work, we binarize all the WALS features, expressing each feature in terms of k binary features, where k is the number of values the original feature can take. Note that beyond the well known issues with feature binarization, this strategy is not optimal for some of the features. For example, the feature 111A *Non-periphrastic Causative Constructions* whose possible values are presented in table 1 would have been better encoded with two binary features rather than four. The question of optimal encoding for the WALS feature set requires expert analysis and will be addressed in future research.

ID	Type	Feature Name	Values
26A	Morphology	Prefixing vs. Suffixing in Inflectional Morphology	Little affixation, Strongly suffixing, Weakly suffixing, Equal prefixing and suffixing, Weakly prefixing, Strong prefixing.
30A	Nominal Categories	Number of Genders	None, Two, Three, Four, Five or more.
83A	Word Order	Order of Object and Verb	OV, VO, No dominant order.
111A	Simple Clauses	Non-periphrastic Causative Constructions	Neither, Morphological but no compound, Compound but no morphological, Both.

Table 1: Examples of WALS features. As illustrated in the table examples, WALS features can take different types of values and may be challenging to encode.

4 Inferring Language Similarities from ESL

Our first goal is to derive a notion of similarity between languages with respect to their native speakers' distinctive structural usage patterns of ESL. A simple way to obtain such similarities is to train a probabilistic NLI model on ESL texts, and interpret the uncertainty of this classifier in distinguishing between a pair of native languages as a measure of their similarity.

4.1 NLI Model

The log-linear NLI model is defined as follows:

$$p(y|x;\theta) = \frac{\exp(\theta \cdot f(x,y))}{\sum_{y' \in Y} \exp(\theta \cdot f(x,y'))} \qquad (1)$$

where y is the native language, x is the observed English document and θ are the model parameters. The parameters are learned by maximizing the L2 regularized log-likelihood of the training data $D = \{(x_1, y_1), ..., (x_n, y_n)\}$.

$$L(\theta) = \sum_{i=1}^{n} \log p(y_i|x_i;\theta) - \lambda \|\theta\|^2 \qquad (2)$$

The model is trained using gradient ascent with L-BFGS-B (Byrd et al., 1995). We use 70% of the FCE data for training and the remaining 30% for development and testing.

As our objective is to relate native language and target language *structures*, we seek to control for biases related to the content of the essays. As previously mentioned, such biases may arise from the essay prompts as well as from various cultural factors. We therefore define the model using only *unlexicalized* morpho-syntactic features, which capture structural properties of English usage.

Our feature set, summarized in table 2, contains features which are strongly related to many of the structural features in WALS. In particular, we use features derived from labeled dependency parses. These features encode properties such as the types of dependency relations, ordering and distance between the head and the dependent. Additional syntactic information is obtained using POS n-grams. Finally, we consider derivational and inflectional morphological affixation. The annotations required for our syntactic features are obtained from the Stanford POS tagger (Toutanova et al., 2003) and the Stanford parser (de Marneffe et al., 2006). The morphological features are extracted heuristically.

4.2 ESL Based Native Language Similarity Estimates

Given a document x and its author's native language y, the conditional probability $p(y'|x;\theta)$ can be viewed as a measure of confusion between languages y and y', arising from their similarity with respect to the document features. Under this interpretation, we derive a language similarity matrix S'_{ESL} whose entries are obtained by averaging these conditional probabilities on the training set documents with the true label y, which we denote as $D_y = \{(x_i, y) \in D\}$.

$$S'_{ESL_{y,y'}} = \begin{cases} \frac{1}{|D_y|} \sum\limits_{(x,y) \in D_y} p(y'|x;\theta) & \text{if } y' \neq y \\ 1 & \text{otherwise} \end{cases} \qquad (3)$$

For each pair of languages y and y', the matrix S'_{ESL} contains an entry $S'_{ESL_{y,y'}}$ which captures the average probability of mistaking y for y', and an entry $S'_{ESL_{y',y}}$, which represents the opposite

Feature Type	Examples
Unlexicalized labeled dependencies	Relation = *prep* Head = *VBN* Dependent = *IN*
Ordering of head and dependent	Ordering = *right* Head = *NNS* Dependent = *JJ*
Distance between head and dependent	Distance = 2 Head = *VBG* Dependent = *PRP*
POS sequence between head and dependent	Relation = *det* POS-between = *JJ*
POS n-grams (up to 4-grams)	POS bigram = *NN VBZ*
Inflectional morphology	Suffix = *ing*
Derivational morphology	Suffix = *ity*

Table 2: Examples of syntactic and morphological features of the NLI model. The feature values are set to the number of occurrences of the feature in the document. The syntactic features are derived from the output of the Stanford parser. A comprehensive description of the Stanford parser dependency annotation scheme can be found in the Stanford dependencies manual (de Marneffe and Manning, 2008).

confusion. We average the two confusion scores to receive the matrix of pairwise language similarity estimates S_{ESL}.

$$S_{ESL_{y,y'}} = S_{ESL_{y',y}} = \frac{1}{2}(S'_{ESL_{y,y'}} + S'_{ESL_{y',y}}) \quad (4)$$

Note that comparable similarity estimates can be obtained from the confusion matrix of the classifier, which records the number of misclassifications corresponding to each pair of class labels. The advantage of our probabilistic setup over this method is its robustness with respect to the actual classification performance of the model.

4.3 Language Similarity Tree

A particularly informative way of representing language similarities is in the form of hierarchical trees. This representation is easier to inspect than a similarity matrix, and as such, it can be more instrumental in supporting linguistic inquiry on language relatedness. Additionally, as we show in section 7, hierarchical similarity trees can outperform raw similarities when used for typology reconstruction.

We perform hierarchical clustering using the Ward algorithm (Ward Jr, 1963). Ward is a bottom-up clustering algorithm. Starting with a separate cluster for each language, it successively merges clusters and returns the tree of cluster merges. The objective of the Ward algorithm is to minimize the total within-cluster variance. To this end, at each step it merges the cluster pair that yields the minimum increase in the overall within-cluster variance. The initial distance matrix required for the clustering algorithm is defined as $1 - S_{ESL}$. We use the Scipy implementation[3] of Ward, in which the distance between a newly formed cluster $a \cup b$ and another cluster c is computed with the Lance-Williams distance update formula (Lance and Williams, 1967).

5 WALS Based Language Similarities

In order to determine the extent to which ESL based language similarities reflect the typological similarity between the native languages, we compare them to similarities obtained directly from the typological features in WALS.

The WALS based similarity estimates between languages y and y' are computed by measuring the cosine similarity between the binarized typological feature vectors.

$$S_{WALS_{y,y'}} = \frac{v_y \cdot v_{y'}}{\|v_y\|\|v_{y'}\|} \quad (5)$$

As mentioned in section 3.2, many of the WALS features do not have values for all the FCE languages. To address this issue, we experiment with two different strategies for choosing the WALS features to be used for language similarity computations. The first approach, called *shared-all*, takes into account only the 32 features that have known values in all the 14 languages of our dataset. In the second approach, called *shared-pairwise*, the similarity estimate for a pair of languages is determined based on the features shared between these two languages.

As in the ESL setup, we use the two matrices of similarity estimates to construct WALS based hierarchical similarity trees. Analogously to the ESL case, a WALS based tree is generated by the

[3] `http://docs.scipy.org/.../scipy.cluster.hierarchy.linkage.html`

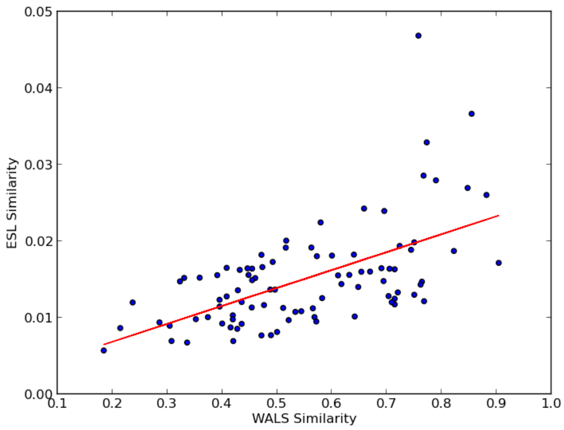


Figure 1: *shared-pairwise* WALS based versus ESL based language similarity scores. Each point represents a language pair, with the vertical axis corresponding to the ESL based similarity and the horizontal axis standing for the typological *shared-pairwise* WALS based similarity. The scores correlate strongly with a Pearson's coefficient of 0.59 for the *shared-pairwise* construction and 0.50 for the *shared-all* feature-set.

Ward algorithm with the input distance matrix $1 - S_{WALS}$.

6 Comparison Results

After independently deriving native language similarity matrices from ESL texts and from typological features in WALS, we compare them to one another. Figure 1 presents a scatter plot of the language similarities obtained using ESL data, against the equivalent WALS based similarities. The scores are strongly correlated, with a Pearson Correlation Coefficient of 0.59 using the *shared-pairwise* WALS distances and 0.50 using the *shared-all* WALS distances.

This correlation provides appealing evidence for the hypothesis that distinctive structural patterns of English usage arise via cross-linguistic transfer, and to a large extent reflect the typological similarities between the respective native languages. The practical consequence of this result is the ability to use one of these similarity structures to approximate the other. Here, we use the ESL based similarities as a proxy for the typological similarities between languages, allowing us to reconstruct typological information without relying on a-priori knowledge about the target language typology.

In figure 2 we present, for illustration purposes, the hierarchical similarity trees obtained with the Ward algorithm based on WALS and ESL similarities. The trees bear strong resemblances to one other. For example, at the top level of the hierarchy, the Indo-European languages are discerned from the non Indo-European languages. Further down, within the Indo-European cluster, the Romance languages are separated from other Indo-European subgroups. Further points of similarity can be observed at the bottom of the hierarchy, where the pairs Russian and Polish, Japanese and Korean, and Chinese and Thai merge in both trees.

In the next section we evaluate the quality of these trees, as well as the similarity matrices used for constructing them with respect to their ability to support accurate nearest neighbors based reconstruction of native language typology.

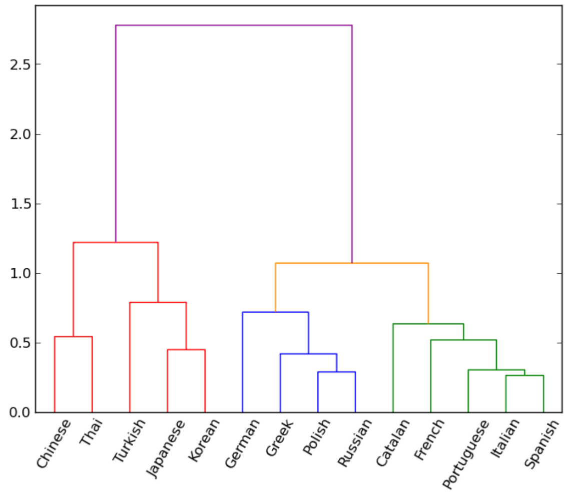
7 Typology Prediction

Although pairwise language similarities derived from structural features in ESL texts are highly correlated with similarities obtained directly from native language typology, evaluating the absolute quality of such similarity matrices and trees is challenging.

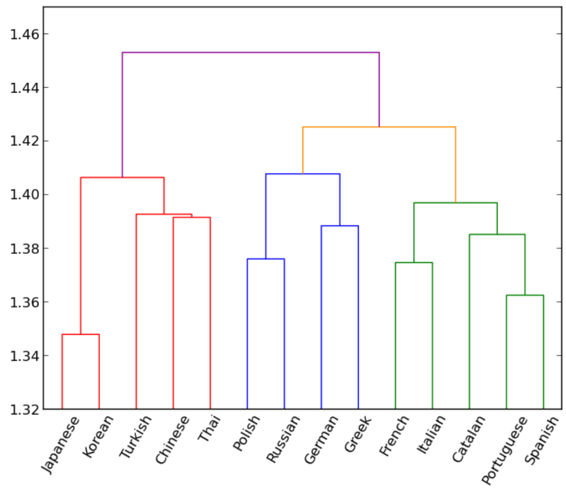
We therefore turn to typology prediction based evaluation, in which we assess the quality of the induced language similarity estimates by their ability to support accurate prediction of unseen typological features. In this evaluation mode we project unknown WALS features to a target language from the languages that are closest to it in the similarity structure. The underlying assumption of this setup is that better similarity structures will lead to better accuracies in the feature prediction task.

Typological feature prediction not only provides an objective measure for the quality of the similarity structures, but also has an intrinsic value as a stand-alone task. The ability to infer typological structure automatically can be used to create linguistic databases for low-resource languages, and is valuable to NLP applications that exploit such resources, most notably multilingual parsing (Naseem et al., 2012; Täckström et al., 2013).

Prediction of typological features for a target language using the language similarity matrix is performed by taking a majority vote for the value of each feature among the K nearest languages of the target language. In case none of the K nearest languages have a value for a feature, or given a tie



(a) Hierarchical clustering using WALS based *shared-pairwise* distances.



(b) Hierarchical clustering using ESL based distances.

Figure 2: Language Similarity Trees. Both trees are constructed with the Ward agglomerative hierarchical clustering algorithm. Tree (a) uses the WALS based *shared-pairwise* language distances. Tree (b) uses the ESL derived distances.

between several values, we iteratively expand the group of nearest languages until neither of these cases applies.

To predict features using a hierarchical cluster tree, we set the value of each target language feature to its majority value among the members of the parent cluster of the target language, excluding the target language itself. For example, using the tree in figure 2(a), the feature values for the target language French will be obtained by taking majority votes between Portuguese, Italian and Spanish. Similarly to the matrix based prediction, missing values and ties are handled by backing-off to a larger set of languages, in this case by proceeding to subsequent levels of the cluster hierarchy. For the French example in figure 2(a), the first fall-back option will be the Romance cluster.

Following the evaluation setups in Daumé III (2009) and Georgi et al. (2010), we evaluate the WALS based similarity estimates and trees by constructing them using 90% of the WALS features. We report the average accuracy over 100 random folds of the data. In the *shared-all* regime, we provide predictions not only for the remaining 10% of features shared by all languages, but also for all the other features that have values in the target language and are not used for the tree construction.

Importantly, as opposed to the WALS based prediction, our ESL based method does not require any typological features for inferring language similarities and constructing the similarity tree. In particular, no typological information is required for the target languages. Typological features are needed only for the neighbors of the target language, from which the features are projected. This difference is a key advantage of our approach over the WALS based methods, which presuppose substantial typological documentation for all the languages involved.

Table 3 summarizes the feature reconstruction results. The ESL approach is highly competitive with the WALS based results, yielding comparable accuracies for the *shared-all* prediction, and lagging only 1.7% – 3.4% behind the *shared-pairwise* construction. Also note that for both WALS based and ESL based predictions, the highest results are achieved using the hierarchical tree predictions, confirming the suitability of this representation for accurately capturing language similarity structure.

Figure 3 presents the performance of the strongest WALS based typological feature completion method, WALS *shared-pairwise* tree, as a function of the percentage of features used for obtaining the language similarity estimates. The figure also presents the strongest result of the ESL method, using the ESL tree, which does not require any such typological training data for obtaining the language similarities. As can be seen, the WALS based approach would require access to almost 40% of the currently documented WALS features to match the performance of the ESL method.

The competitive performance of our ESL method on the typology prediction task underlines

Method	NN	3NN	Tree
WALS *shared-all*	71.6	71.4	69.1
WALS *shared-pairwise*	73.1	74.1	**74.2**
ESL	71.4	70.7	**72.2**

Table 3: Typology reconstruction results. Three types of predictions are compared, nearest neighbor (NN), 3 nearest neighbors (3NN) and nearest tree neighbors (Tree). WALS *shared-all* are WALS based predictions, where only the 32 features that have known values in all 14 languages are used for computing language similarities. In the WALS *shared-pairwise* predictions the language similarities are computed using the WALS features shared by each language pair. ESL results are obtained by projection of WALS features from the closest languages according to the ESL language similarities.

its ability to extract strong typologically driven signal, while being robust to the partial nature of existing typological annotation which hinders the performance of the baselines. Given the small amount of ESL data at hand, these results are highly encouraging with regard to the prospects of our approach to support typological inference, even in the absence of any typological documentation for the target languages.

8 Conclusion and Outlook

We present a novel framework for utilizing cross-linguistic transfer to infer language similarities from morpho-syntactic features of ESL text. Trading laborious expert annotation of typological features for a modest amount of ESL texts, we are able to reproduce language similarities that strongly correlate with the equivalent typology based similarities, and perform competitively on a typology reconstruction task.

Our study leaves multiple questions for future research. For example, while the current work examines structure transfer, additional investigation is required to better understand lexical and phonological transfer effects.

Furthermore, we currently focuse on native language typology, and assume English as the foreign language. This limits our ability to study the constraints imposed on cross-linguistic transfer by the foreign language. An intriguing research direction would be to explore other foreign languages and compare the outcomes to our results on English.

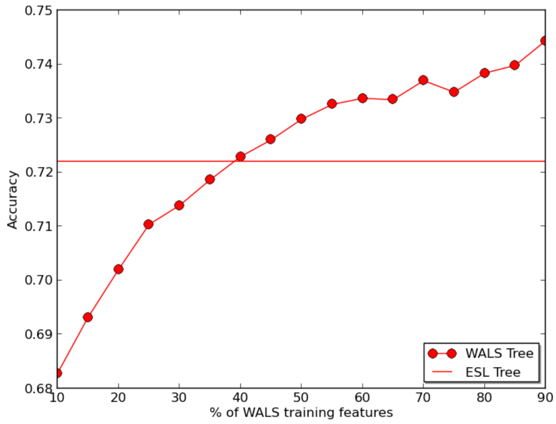


Figure 3: Comparison of the typological feature completion performance obtained using the WALS tree with *shared-pairwise* similarities and the ESL tree based typological feature completion performance. The dotted line represents the WALS based prediction accuracy, while the horizontal line is the ESL based accuracy. The horizontal axis corresponds to the percentage of WALS features used for constructing the WALS based language similarity estimates.

Finally, we plan to formulate explicit models for the relations between specific typological features and ESL usage patterns, and extend our typology induction mechanisms to support NLP applications in the domain of multilingual processing.

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