Turning Transfer Inside Out: What NLP Reveals About Typology

Nafiseh Momeni Mohammadabadi Guillaume Wisniewski
LLF, CNRS and Université Paris-Cité, F-75013 Paris, France
nafiseh.momeni-mohammadabadi@etu.u-paris.fr
guillaume.wisniewski@u-paris.fr

RÉSUMÉ

We investigate cross-lingual transfer by reversing the usual perspective: instead of predicting which source language suits a given target, we leverage part-of-speech transfer performance to infer typological similarities between languages. Using a regression model combined with SHAP value explanations, we show that transfer scores reveal consistent linguistic regularities. Our approach demonstrates that NLP systems can complement typological databases by uncovering structural patterns and helping to identify suitable source languages without exhaustive experimentation.

MOTS-CLÉS : transfert interlingue, typologie linguistique, valeurs SHAP.

KEYWORDS: cross-lingual transfer, linguistic typology, SHAP values.

1 Introduction

Multilingual language models, such as `mBERT` (Devlin *et al.*, 2019) and `XLM-R` (Conneau & Lample, 2019), have opened new avenues for NLP, most notably in cross-lingual transfer, as exemplified by the seminal work of Pires *et al.* (2019): training a system on one language (e.g., PoS tagging, dependency parsing, NER) and applying it to another. This is made possible by shared multilingual representations at the sub-token level, which allow fine-tuning on a source language and transfer to a target. Remarkably, such correspondences emerge from unsupervised pretraining, without explicit cross-lingual supervision. This raises fundamental questions: why do these properties arise, and how are they shaped by linguistic similarity?

Previous work (e.g., (Lin *et al.*, 2019)) has largely focused on predicting which source language transfers best to a given target, often leveraging typological resources such as `WALS`. Our goal is to invert this perspective: can transfer performance itself reveal typological information? This question matters for both theory and practice. Theoretically, it tests whether model behaviour reflects genuine linguistic properties. Practically, it offers a way to complement incomplete or inconsistent typological databases by predicting missing or erroneous features.

In this preliminary study, we analyse cross-lingual PoS tagging on Universal Dependencies. We show that transfer performance aligns with known language families, suggesting that NLP systems can also serve as tools for linguistic discovery.

2 Method for Analysing Transfer

Datasets and Models In this preliminary work, we restrict our investigation to PoS tagging and rely on models developed within the `UDPipe` project (Straka, 2018). `UDPipe` offers trainable pipelines for tokenisation, tagging, lemmatisation, and dependency parsing, trained on the treebanks provided by the Universal Dependencies (UD) initiative (Zeman *et al.*, 2025).[1] Its PoS tagger combines word embeddings with character-level representations within a neural architecture, which has been shown to generalise well across typologically diverse languages.

The `UDPipe` authors make available trained models for all UD training corpora, covering 147 models across 78 very diverse languages. Note that in, in the UD project, some languages are represented by multiple corpora (up to 10 corpora for languages English and Italian) and some corpora contain only a test set (and no train set). Our first step was therefore to estimate the accuracy obtained when a PoS tagger trained on corpus A is applied to one of the 296 test sets from a corpus B (spanning 168 languages), independently of whether A and B belong to the same language. This procedure yielded a total of 43,512 transfer scores.[2] As a baseline, we considered the most frequent tag in the training data. For our experiments, we retained only those results above baseline, which account for 55% of all scores.

Model The task we address is to predict the performance of a PoS tagger trained on a source language A when applied to a corpus in a target language B. We formulate this as a regression problem, where the goal is to predict a real-valued score from features representing the language pair (A, B). In our experiments, we employ an Histogram-based Gradient Boosting Regression Tree.[3]. This regressor is an ensemble method based on decision trees and gradient boosting, particularly well-suited for heterogeneous and large datasets and robust to missing values, properties that strongly motivated our choice. We trained the model with maximum depth of 10 on 80% of the available language pairs, and evaluated it on the remaining 20% (which amounts to 96 target languages). For languages with multiple corpora, we average the observed transfer performance to obtain a single label per pair.

We evaluate the model's predictive capacity in two ways. First, we report the coefficient of determination (R^2), which quantifies how well the predicted scores approximate the gold

[1] We use the version 2.15 of the UD Project.

[2] All systems are evaluated by their F_1 scores on `UPOS` metric computed by the official CoNLL shared task on universal dependency parsing.

[3] More precisely, we used the implementation provided by `scikit-learn` (Pedregosa *et al.*, 2011).

values. Secondly, we compute a top-k measure designed to assess the practical usefulness of the predictions for source language selection. For each target language, we identify the best source language according to empirical transfer and check whether it appears among the k highest-ranked predictions of the regressor. The top-k score thus corresponds to the proportion of cases where the predicted ranking successfully includes the gold-best source. While the R^2 metric evaluates the accuracy of numerical predictions, the top-k measure tests whether our approach can be used to automatically select an appropriate source language for a given target.

Features We represent each pair by a set of features designed to capture two types of information. The first type relates exclusively to the datasets themselves, and cover features such as the size of the training corpus or the number of different PoS used in this dataset. Theses features aim at controlling for factors that do not directly stem from linguistic properties. The second type corresponds to linguistic features extracted from `lang2vec` (Littell *et al.*, 2017) and `Grambank` (Skirgård *et al.*, 2023). `lang2vec` provides typological, geographical, and phylogenetic features derived from several linguistic resources, while `Grambank` encodes structural properties of languages in a large-scale typological database.

The features fall into five categories. We first include individual vectors for source and target languages from `lang2vec` and `Grambank`, along with binary indicators of feature agreement (`NaN` if missing, 1 if identical, 0 otherwise). Pairwise similarity metrics are then computed using cosine and Gower (Gower, 1971) scores over shared features, covering syntax, phonetics, phonology, and an overall average similarity. In addition, we measure family similarity through cosine similarity over typological group encodings, and geographic distance using the coordinates provided in `lang2vec`. In total, each language pair is represented by 1,464 features (968 linguistic features and 6 dataset features and 7 similarity features). A complete list of these features is available in our source code, which will be released alongside the publication of this article.

3 Experimental Results

Predicting PoS Accuracy We began by evaluating our ability to predict the performance on a dataset in language B using a PoS tagger trained on language A. The results are encouraging: across all languages in the test corpus, our regressor achieves an R^2 of 0.82, indicating that the predicted scores closely match the observed scores on the test sets. Even more strikingly, our approach attains a top-1 accuracy of 0.42 and a top-5 accuracy of 0.88, demonstrating that our system can reliably identify the most suitable source corpus without the need to train or test every possible system. We further employed SHAP values (Mosca *et al.*, 2022), a model-agnostic explanation technique that quantifies the contribution of each input feature to individual predictions, to determine which features were

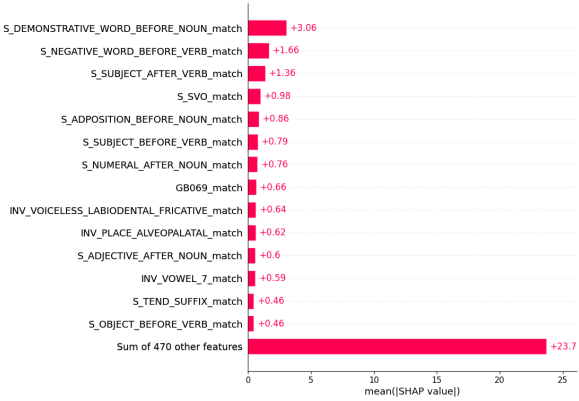

Figure 1: Feature importance for our regressor.

most influential in guiding the regressors decisions. As shown in Figure 1, these analyses reveal that the regressors decisions are primarily driven by linguistic features, especially those capturing word order, which is consistent with the nature of the task.

Predicting Linguistics Features from PoS Performance In a second series of experiments, we attempted to predict the similarity family defined as the distance between feature representations describing language typologyusing the same type of regressor but relying on a single feature only. Our model achieves an R^2 of 0.28, which at first sight may appear low. However, a more fine-grained analysis reveals a $\texttt{top}{-}1$ accuracy of 0.22 and a $\texttt{top}{-}5$ accuracy of 0.67, indicating that the system still captures a substantial proportion of the underlying similarity structure and can rank plausible candidates effectively. These results compare to those obtained when considering the six similarity measures derived from `lang2vec` and `Grambank`: in this case the regressor attains an R^2 of 0.60, a $\texttt{top}{-}1$ accuracy of 0.36, and a $\texttt{top}{-}5$ accuracy of 0.77. This performance is only marginally better than what we obtain from a single PoS-based score, despite the greater modelling capacity (the number of features is higher) and the use of features directly related to the prediction target. This observation suggests that the relatively modest performance we report may be partly explained by the way the task has been formulated (in particular our decision to average scores across multiple corpora for each language) as well as by potential noise in the annotations of `lang2vec` and `Grambank`.

4 Conclusion

Our experiments show that cross-lingual transfer performance reflects robust linguistic similarities, even with a relatively simple model. These findings suggest that NLP systems

can enrich or correct existing typological resources. In the longer term, this approach could facilitate automatic source-language selection and deepen our understanding of the links between typology and transfer.

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