Automatic Extraction of Rules Governing Morphological Agreement

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Abstract

Creating a descriptive grammar of a language is an indispensable step for language documentation and preservation. However, at the same time it is a tedious, time-consuming task. In this paper, we take steps towards automating this process by devising an automated framework for extracting a first-pass grammatical specification from raw text in a concise, human- *and* machine-readable format. We focus on extracting rules describing *agreement*, a morphosyntactic phenomenon at the core of the grammars of many of the world's languages. We apply our framework to all languages included in the Universal Dependencies project, with promising results. Using cross-lingual transfer, even with no expert annotations in the language of interest, our framework extracts a grammatical specification which is nearly equivalent to those created with large amounts of gold-standard annotated data. We confirm this finding with human expert evaluations of the rules that our framework produces, which have an average accuracy of 78%. We release an interface demonstrating the extracted rules at https://neulab.github.io/lase/. The code is publicly available here.[1]

1 Introduction

While the languages of the world are amazingly diverse, one thing they share in common is their adherence to grammars — sets of morpho-syntactic rules specifying how to create sentences in the language. Hence, an important step in the understanding and documentation of languages is the creation of a *grammar sketch*, a concise and human-readable description of the unique characteristics of that particular language (e.g. Huddleston (2002) for English, or Brown and Ogilvie (2010) for the world's languages).

One aspect of morphosyntax that is widely described in such grammatical specifications is *agreement*, the process wherein a word or morpheme selects morphemes in correspondence with another word or phrase in the sentence (Corbett, 2009). Languages have varying degrees of agreement ranging from none (e.g. Japanese, Malay) to a large amount (e.g. Hindi, Russian, Chichewa). Patterns of agreement also vary across syntactic subcategories. For instance, regular verbs in English agree with their subject in number and person but modal verbs such as "will" show no agreement.

Having a concise description of these rules is of obvious use not only to linguists but also language teachers and learners. Furthermore, having such descriptions in machine-readable format will further enable applications in natural language processing (NLP) such as identifying and mitigating gender stereotypes in morphologically rich languages (Zmigrod et al., 2019).

The notion of describing a language "in its own terms" based solely on raw data has an established tradition in descriptive linguistics (e.g. Harris (1951)). In this work we present a framework (outlined in Figure 1) that *automatically* creates a first-pass specification of morphological agreement rules for various morphological features (Gender, Number, Person, etc.) from a raw text corpus for the language in question. First, we perform syntactic analysis, predicting part-of-speech (POS) tags, morphological features, and dependency trees. Using this analyzed data, we then learn an agreement prediction model that contains the desired rules. Specifically, we devise a binary classification problem of identifying whether agreement will be observed between a head and its dependent token on a given morphological property. We use decision trees as our classification model because

[1]https://github.com/Aditi138/LASE-Agreement

†: Work done at Carnegie Mellon University.

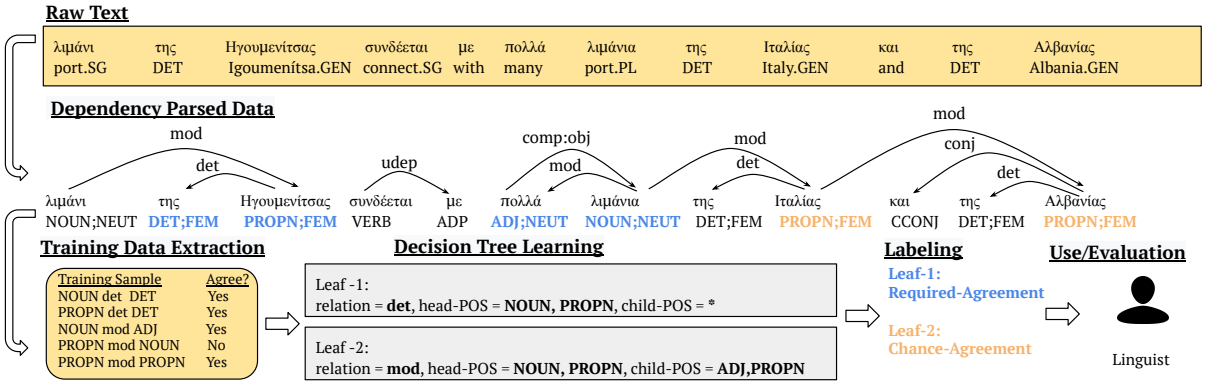

Figure 1: An overview of our method's workflow for gender agreement in Greek. The example sentence translates to "The port of Igoumenitsa is connected to many ports in Italy and Albania." First, we dependency parse and morphologically analyze raw text to create training data for our binary agreement classification task. Next, we learn a decision tree to extract the rule set governing gender agreement, and label the extracted leaves as either representing required or chance agreement. Finally these rules are presented to a linguist for perusal.

they are easy to interpret and we can easily *extract* the classification rules from the tree leaves to get an initial set of potential agreement rules. Finally, we perform *rule labeling* of the extracted rules, identifying which tree leaves correspond to probable agreement. This is required because not all agreeing head/dependent token pairs are necessarily due to some underlying rule. For instance, in Figure 1's example of Greek gender agreement, both the head and its dependent token Ιταλίας→Αλβανίας have feminine gender, but this agreement is purely by-chance, as correctly identified by our framework.

The quality of the learnt rules depends crucially on the quality and quantity of dependency parsed data, which is often not readily available for low-resource languages. Therefore, we experiment with not only gold-standard treebanks, but also trees generated automatically using models trained using cross-lingual transfer learning. This assesses the applicability of the proposed method in a situation where a linguist may want to explore the characteristics of agreement in a language that does not have a large annotated dependency treebank.

We evaluate the correctness of the extracted rules conducting human evaluation with linguists for Greek, Russian, and Catalan. In addition to the manual verification, we also devise a new metric for automatic evaluation of the rules over unseen test data. Our contributions can be summarized to:

1. We propose a framework to automatically extract agreement rules from raw text, and release these rules for 55 languages as part of an interface[2] which visualizes the rules in detail along with examples and counter-examples.
2. We design a human evaluation interface to allow linguists to easily verify the extracted rules. Our framework produces a decent first-pass grammatical specification with the extracted rules having an average accuracy of 78%. We also devise an automated metric to evaluate our framework when human evaluation is infeasible.
3. We evaluate the quality of extracted rules under real zero-shot conditions (on Breton, Buryat, Faroese, Tagalog, and Welsh) as well as low-resource conditions (with simulation experiments on Spanish, Greek, Belarusian and Lithuanian) varying the amount of training data. Using cross-lingual transfer, rules extracted with as few as 50 sentences with gold-standard syntactic analysis are nearly equivalent to the rules extracted when we have hundreds/thousands of gold-standard data available.

2 Problem Formulation

For a head h and a dependent d that are in a dependency relation r, we will say that they *agree* on a morphological property f if they share the same value for that particular property i.e. $f_h = f_d$. Some agreements that we observe in parsed data can be attributed to an underlying grammatical rule. For example, in Figure 2 the Spanish A.1 shows an example of where subject (*enigmas)* and verb (*son*) need to agree on number. We will refer to such rules as *required-agreement*. Such a required agreement rule dictates that an example like A.2 is ungrammatical and would not appear in well-formed Spanish sentences, since the subject and

[2] https://neulab.github.io/lase/

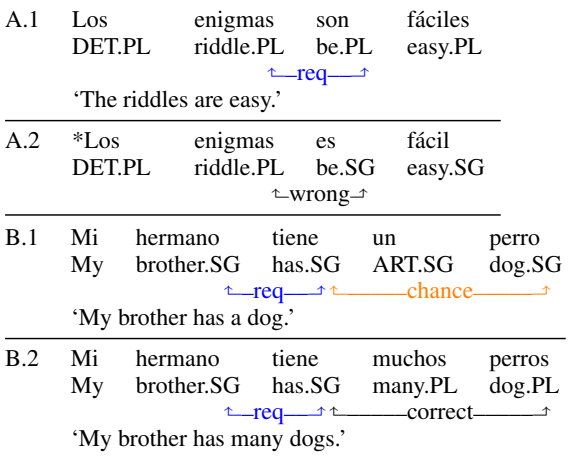

Figure 2: Subject-verb number agreement is required in Spanish, as in example A.1, which renders example A.2 ungrammatical. Object-verb agreement is not required, so both B.1 and B.2 are grammatical. The object and the verb in B.1 only agree by chance.

the verb do not have the same number marking. However, not all word pairs that agree do so because of some underlying rule, and we will refer to such cases as *chance-agreement*. For example, in Figure 2 the object (*perro*) and verb (*tiene*) in B.1 only agree in number by chance, and example B.2 (where the object of a singular verb is plural) is perfectly acceptable.

Our goal is to extract, from textual examples, the set of *rules* $\mathcal{R}_l^f$ that concisely describe the agreement process for language l. Concretely, this will indicate for which head-dependent pairs the language displays *required-agreement* and for which we will observe at most *chance-agreement*. Canonically, agreement rules are defined over syntactic features of a language as seen in Figure 2 where we have the following rule for Spanish: "subjects agree with their verbs on number".[3] To formalize this notion, we define a *rule* to be a set of features which are defined over the dependency relation, head and dependent token types. In this paper, we make the simplifying assumption that head and dependent tokens are represented by only part-of-speech features, as we would like our extracted rules to be *concise* and easily interpretable downstream, although this assumption could be relaxed in future work.

The rule discovery process consists of two major steps: a *rule extraction* step followed by a *rule labeling* and *merging* step (also see Figure 1).

[3]Sometimes semantic features are used for agreement for eg. *United Nations is*, despite *United Nations* being plural, it is treated as singular for purposes of agreement.

2.1 Rule Extraction

To create our training data for rule extraction, we first annotate raw text with part-of-speech (POS) tags, morphological analyses, and dependency trees. We then base our training data on these annotations by converting each dependency relation into a triple $\langle h, d, r \rangle$, indicating the head token, dependent/child token, and dependency relation between h and d respectively. From the whole treebank, we now have input features $X_f = \{\langle h_1, d_1, r_1 \rangle, \ldots, \langle h_n, d_n, r_n \rangle\}$ and binary output labels $Y{=}y_1, \ldots, y_n$, where if the head and the dependent token agree on feature f (such that $f_h{=}f_d$) we set $y = 1$, otherwise $y = 0$. We filter out the tuples where either of the linked tokens does not display the morphological feature f.

We train a model for $p(Y|X)$ using decision trees (Quinlan, 1986) using the CART algorithm (Breiman et al., 1984). A major advantage of decision trees is that they are easy to interpret and we can visualize the exact features used by the decision tree to split nodes. The decision tree induces a distribution of agreement over training samples in each leaf, e.g. 99% agree, 1% not agree in Leaf-3 for gender agreement in Spanish (Figure 3(a)).

2.2 Rule Labeling

Now that we have constructed a decision tree where each tree leaf corresponds to a salient partition of the possible syntactic structures in the language, we then label these tree leaves as *required-agreement* or *chance-agreement*. For this we apply a threshold on the ratio of agreeing training samples within a leaf – if the ratio exceeds a certain number the leaf will be judged as *required-agreement*. We experiment with two types of thresholds:

Hard Threshold: We set a hard threshold on the ratio that is identical for all leaves. In all experiments, we set this threshold to 90% based on manually inspecting some resulting trees to find a threshold that limited the number of non-agreeing syntactic structures being labeled as *required-agreement*.

Statistical Threshold: Leaves with very few examples may exceed the hard threshold purely by chance. In order to better determine whether the agreements are indeed due to a true pattern of required agreement, we devise a thresholding strategy based on significance testing. For all agreement-majority leaves, we apply a chi-squared goodness of fit test to compare the observed output distri-

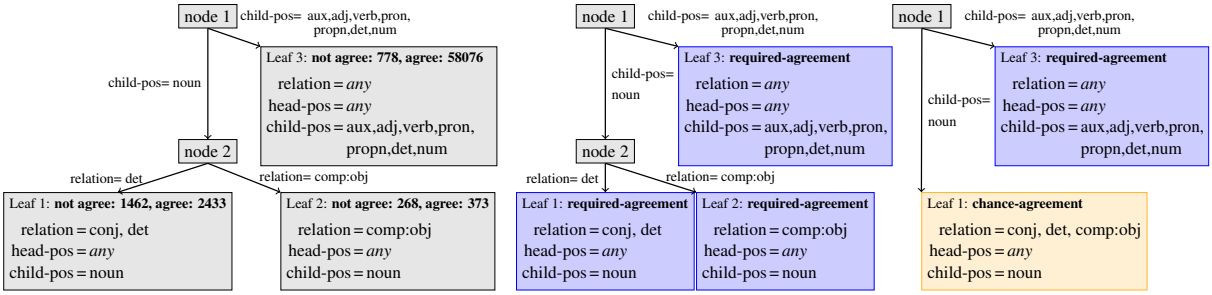

Figure 3: Extracting gender agreement rules in Spanish. (a) A decision tree is learned over dependency link triples, inducing a distribution of agreement over examples in each leaf. However, simple majority voting leads to false positives: Leaf-1 includes more agreeing data points, but in reality this agreement is purely by chance. (b) With a statistically-inspired threshold to label the leaves, Leaf-1 gets correctly labeled as *chance-agreement*. (c) We merge leaves with the same label to get a concise representation. Every dependency link triple receives the label of the unique leaf it falls under.

bution with an expected probability distribution specified by a null hypothesis. Our null hypothesis H_0 will be that any agreement we observe is due to chance. If we reject the null hypothesis, we will conclude from the alternate hypothesis H_1 that there exists a grammatical rule requiring agreement for this leaf's cases:

H_0 : The leaf has *chance-agreement*.

H_1 : The leaf has *required-agreement*.

If there is no rule requiring agreement, we assume that the morphological properties of the head and the dependent token are independent and identically distributed discrete random variables following a categorical distribution. We compute the probability of chance agreement based on the number of values that the specific morphological property f can take. Since morphological feature values are not equally probable, we use a probability proportional to the *observed* value counts. For a binary number property where 90% of all observed occurrences are singular and 10% are plural, the probability of chance agreement is equal to 0.82=0.9×0.9+0.1×0.1, which gives the observed output distribution p=$[0.18, 0.82]$. Using p we compute the expected frequency count $E_i = np_i$ where n is the total number of samples in the given leaf, i=$[0, 1]$ is the output class of the leaf, and p_i is the hypothesized proportion of observations for class i. The chi-squared test calculates the test statistic χ^2 as follows:

$$\chi^2 = \sum_{i\in[0,1]} \frac{(O_i - E_i)^2}{E_i}$$

where O_i is the observed frequency count in the given leaf. The test outputs a p-value, which is the probability of observing a sample statistic as extreme as the test statistic. If the p-value is smaller than a chosen significance level (we use 0.01) we reject the null hypothesis and label the leaf as *required-agreement*.

The chi-squared test especially helps in being cautious with leaves with very few examples. However, for leaves with larger number of examples statistical significance alone is insufficient, because there are a large number of cases where there are small but significant differences from the ratio of agreement expected by chance.[4] Therefore, in addition to comparing the p-value we also compute the *effect size* which provides a quantitative measure on the magnitude of an effect (Sullivan and Feinn, 2012). Cramér's phi ϕ_c (Cramér, 1946) is a commonly used method to measure the *effect size*:

$$\phi_c = \frac{\chi^2}{N(k-1)}$$

where χ^2 is the test statistic computed from the chi-squared test, N is the total number of samples within a leaf, and k is the degree of freedom (which in this case is 2 since we have two output classes). Cohen (1988) provides rules of thumb for interpreting these effect size. For instance, $\phi_c > 0.5$ is considered to be a large effect size and a large effect size suggests that the difference between the two hypotheses is important. Therefore, a leaf is labeled as *required-agreement* when the p-value is less than the significance value and the effect size is greater than 0.5. Now Leaf-1 in Figure 3(b) is correctly identified as *chance-agreement*.

[4]One limitation of this is that rules that show agreement *sometimes* get incorrectly labeled as either *chance-agreement* or *required-agreement*. We consider this in evaluation, but predicting sometimes agreement is relegated to future work.

Rule Merging: Because we are aiming to have a concise, human-readable representation of agreement rules of a language, after labeling the tree leaves we merge sibling leaves with the same label as shown in Figure 3(c). Further, we collapse tree nodes having all leaves with the same label thereby reducing the apparent depth of the tree.

3 Experimental Settings and Evaluation

Our experiments aim to answer the following research questions: (1) can our framework extract linguistically plausible agreement rules across diverse languages? and (2) can it do so even if gold-standard syntactic analyses are not available? To answer the first question we evaluate rules extracted from gold-standard syntactic analysis (Sec. §4). For the second question we experiment in low-resource and zero-shot scenarios using cross-lingual transfer to obtain parsers on the languages of interest, and evaluate the effect of noisy parsing results on the quality of rules (Sec. §5).

3.1 Settings

Data We use the Surface-Syntactic Universal Dependencies (SUD) treebanks (Gerdes et al., 2018, 2019) as the gold-standard source of complete syntactic analysis. The SUD treebanks are derived from Universal Dependencies (UD) (Nivre et al., 2016, 2018), but unlike the UD treebanks which favor content words as heads, the SUD ones express dependency labels and links using purely syntactic criteria, which is more conducive to our goal of learning syntactic rules. We use the tool of Gerdes et al. (2019) to convert UD v.2.5 (Nivre et al., 2020) into SUD. We only use the training portion of the treebanks for learning our rules.

Rule Learning We use `sklearn`'s (Pedregosa et al., 2011) implementation of decision trees and train a separate model for each morphological feature f for a given language. We experiment with six morphological features (Gender, Person, Number, Mood, Case, Tense) which are most frequently present across several languages. We perform a grid search over the decision tree parameters (detailed in Appendix A.1) and select the model performing best on the validation set. We report results with the *Statistical Threshold* because on manual inspection we find the trees to be more reliable than the ones learnt from the *Hard Threshold* (see Appendix A.5 for an example).

3.2 Evaluation

We explore two approaches to evaluate the extracted rules, one based on expert annotations, and an automated proxy evaluation.

Expert Evaluation Ideally, we would collect annotations for all head-relation-dependent triples in a treebank, but this would involve annotating hundreds of triples, requiring a large time commitment from linguists in each language we wish to evaluate. Instead, for each language/treebank we extract and evaluate the top 20 most frequent "head POS, dependency relation, dependent POS" triples for the six morphological features amounting to 120 sets of triples to be annotated.[5] We then present these triples with 10 randomly selected illustrative examples and ask a linguist to annotate whether there is a rule in this language governing agreement between the head-dependent pair for this relation. The allowed labels are: *Almost always agree* if the construction must almost always exhibit agreement on the given feature; *Sometimes agree* if the linked arguments sometimes must agree, but sometimes do not have to; *Need not agree* if any agreement on the feature is random. An example of the annotation interface is shown in the Appendix A.2.

For each of the human annotated triples in feature f, we extract the label assigned to it by the learnt decision tree $\mathcal{T}$. We find the leaf to which the given triple t belongs and assign that leaf's label to the triple, referred by $l_{\text{tree},f,t}$. The human evaluation score (HS) for each triple marking feature f is given by:

$$\text{HS}_{f,t} = \mathbb{1} \begin{cases} 1 & l_{\text{human},f,t} = l_{\text{tree},f,t} \\ 0 & \text{otherwise} \end{cases}$$

where $l_{\text{human},f,t}$ is the label assigned to the triple t by the human annotator. These scores are then averaged across all annotated triples T_f to get the human evaluation metric (HRM) for feature f

$$\text{HRM}_f = \frac{\sum_{t \in T_f} \text{HS}_{f,t}}{|T_f|}.$$

Automated Evaluation As an alternative to the infeasible manual evaluation of all rules in every language, we propose an *automated rule metric* (ARM) that evaluates how well the rules extracted from decision tree $\mathcal{T}$ fit to unseen gold-annotated test data. For each triple t marking feature f, we

[5] The top 20 most frequent triples covered approximately 95% of the triples where this feature was active on average.

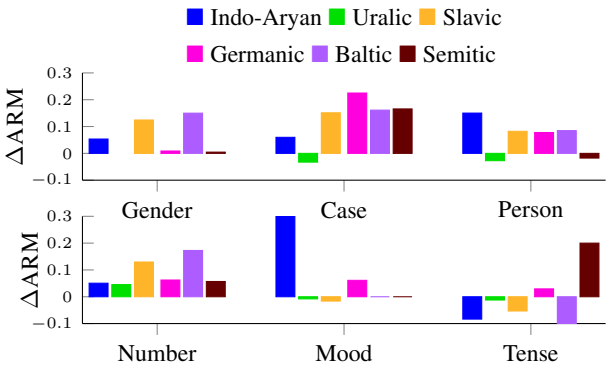

Figure 4: Difference in the ARM scores of decision trees over gold-standard syntactic analysis with baseline trees where all leaves predict *chance-agreement*.

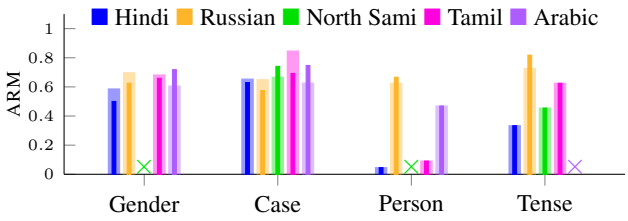

Figure 5: Our approach (shaded bars) outperforms the chance-agreement baseline (solid bars) in all cases where there exist agreement rules. Features not present in the language are marked with ×.

first retrieve all examples from the test data corresponding to that triple. Next, we calculate the empirical agreement by counting the fraction of test samples that exhibit agreement, referred by $q_{f,t}$. For a *required-agreement* leaf, we expect most test samples satisfying that rule to show agreement.[6] To account for any exceptions to the rule and/or parsing-related errors, we use a threshold that acts as proxy for evaluating whether the given triple denotes *required agreement*. We use a threshold of 0.95, and if $q_{f,t} > 0.95$ then we assign the test label $l_{\text{test},f,t}$ for that triple as *required-agreement*, and otherwise choose *chance-agreement*.[7] Similar to the human evaluation, we compute a score for each triple t marking feature f

$$\text{AS}_t = \mathbb{1} \begin{cases} 1 & l_{\text{test},f,t} = l_{\text{tree},f,t} \\ 0 & \text{otherwise} \end{cases}$$

then average scores across all annotated triples in T_f to get the ARM score for each feature f:

$$\text{ARM}_f = \frac{\sum_{t \in T_f} \text{AS}_t}{|T_f|}$$

4 Experiments with Gold-Standard Data

In this section, we evaluate the quality of the rules induced by our framework, using gold-standard syntactic analyses and learning the decision trees over triples obtained from the training portion of all SUD treebanks. As baseline, we compare with trees predicting all leaves as *chance-agreement*.

[6]There are exceptions: e.g. when the head of dependent is a multiword expression (MWE), in which case dependency parsers might miss or pick only one of its constituents as head/dependent, or if the MWE is syntactically idiosyncratic.

[7]We keep a 5% margin to account for any exceptions or parsing errors based on the feedback given by the annotators.

The extracted rules have an 0.574 ARM score (averaged across all treebanks and features), outperforming the baseline scores by 0.074 ARM points.[8] Of all the 451 decision trees across all treebanks and features, we find 78% trees outperforming the baseline trees. In Figure 4, we show the improvements over the baseline averaged across language families/genera. In families with extensive agreement systems such as Slavic and Baltic our models clearly outperform the baseline discovering correct rules, as they do for the other Indo-European genera, Indo-Aryan and Germanic. For mood and tense, the *chance-agreement* baseline performs on par with our method. This is not surprising because there is little agreement observed for these features given that only verbs and auxiliary verbs mark these features. We find that for both tense and mood in the Indo-Aryan family, our model identifies *required-agreement* primarily for conjoined verbs, which mostly need to agree only if they share the same subject. However, subsequent analysis revealed that in the treebanks nearly 50% of the agreeing verbs do not share the same subject but do agree by chance.

Agreement for Indo-European languages like Hindi and Russian is well documented (Comrie, 1984; Crockett, 1976) and is reflected in our large improvements over the baseline (Figure 5). Similarly, Arabic exhibits extensive agreement on noun phrases including determiners and adjectives (Aoun et al., 1994). We find that for Arabic gender the lower ARM scores of our method are an artifact of the small test data.

North Sami is an interesting test bed: as a Uralic language, case agreement would be somewhat unexpected and indeed our model's predictions are not better than the baseline. Nevertheless, with our interface we find patterns of rare positive paratactic constructions with required agree-

[8]Individual scores for each treebank are in Appendix A.5.

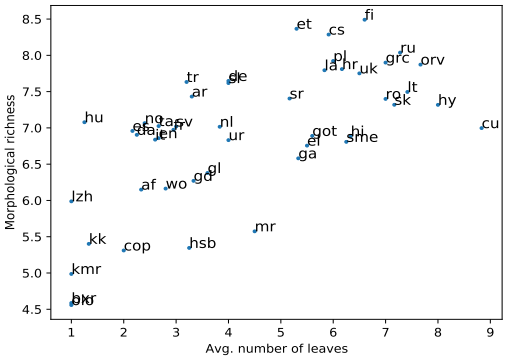

Figure 6: Correlation between size of the decision trees constructed by our framework and morphological complexity of languages.

ment where demonstrative pronouns overwhelmingly agree with their heads.[9] The case decision tree also uncovers interesting patterns of 100% agreement on Tamil constructions with nominalized verbs (Gerunds) where the markings propagate to the whole phrase.

Conciseness of Extracted Rules We further analyze the decision trees learnt by our framework for conciseness and find that the trees grow more complex with increasing morphological complexity of languages as seen in Figure 6. To compute the morphological complexity of a language, we use the word entropy measure proposed by Bentz et al. (2016) which measures the average information content of words and is computed as follows:

$$H(D) = -\sum_{i \in V} p(w_i) \log p(w_i)$$

where V is the vocabulary, D is the monolingual text extracted from the training portion of the respective treebank, $p(w_i)$ is the word type frequency normalized by the total tokens. Since this entropy doesn't account for unseen word types, Bentz et al. (2016) use the *James-Stein shrinkage* estimator (Hausser and Strimmer, 2009) to calculate $p(w_i)$:

$$p(w_i) = \lambda p^{\text{target}}(w_i) + (1 - \lambda) p^{\text{ML}}(w_i)$$

where $\lambda \in [0, 1]$, p^{target} denotes the maximum entropy case given by the uniform distribution $\frac{1}{V}$ and p^{ML} is the maximum likelihood estimator which is given by the normalized word type frequency. Languages with a larger word entropy are considered to be morphologically rich as they pack more information into the words. In Figure 6 we plot the morphological richness with the average number of leaves across all features and find these to be highly correlated.

Manual Evaluation Results We conduct an expert evaluation for Greek (el), Russian (ru) and Catalan (ca) as described in Section §3.2. For a strict setting, we consider both *Sometimes agree* and *Need not agree* as *chance-agreement* and report the human evaluation metric (HRM) in Figure 7. Overall, our method extracts first-pass grammar rules achieving 89% accuracy for Greek, 78% for Russian and 66% for Catalan.

In most error cases, like person in Russian, our model produces *required-agreement* labels, which we can attribute to skewed data statistics in the treebanks. In Russian and Greek, for instance, conjoined verbs only need to agree in person and number if they share the same subject (in which case they *implicitly* agree because they both must agree with the same subject phrase). In the treebanks, though, only 15% of the agreeing verbs do indeed share the same subject – the rest agree by chance. In a reverse example from Catalan, the overwhelming majority (92%) of 8650 tokens are in the third-person, causing our model to label all leaves as chance agreement despite the fact that person/number agreement is required in such cases. Similarly for tense in Catalan, our framework predicts *chance-agreement* for auxiliary verbs with verbs as their dependent because of overwhelming majority of disagreeing examples. We believe this is because of both annotation artifact and the way past tense is realized.

To demonstrate how well the automated evaluation correlates with the human evaluation protocol, we compute the Pearson's correlation (r) between the ARM and HRM for each language under four model settings: *simulate-50, simulate-100, baseline* and *gold*. *simulate-x* is a simulated low-resource setting where the model is trained using x gold-standard syntactically analysed data.[10] The *baseline* setting is the one where all leaves predict *chance-agrement* and under the *gold* setting we train using the entire gold-standard data. We compute the ARM and HRM scores for the rules learnt under each of the four settings and report the Pearson's correlation, averaged across all features. Overall, we observe a moderate correlation for all three languages, with $r = 0.59$ for Greek, r=0.41 for Russian and r=0.38 for Catalan. The correla-

[9] Leaf 3 here: https://bit.ly/34mHTeG

[10] More details on the experimental setup in § 5.1.

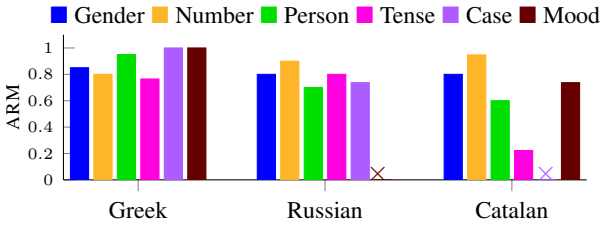

Figure 7: Annotation accuracy for Greek, Russian and Catalan per each morphological feature.

tions are very strong for some features such as Gender (r_{el}=0.97, r_{ru}=0.82, r_{ca}=0.98) and Number (r_{el}=0.97, r_{ru}=0.69, r_{ca}=0.96) where we expect to see extensive agreement.

5 Low-Resource Experiments

5.1 Simulated Zero-/Few-Shot Experiments

It is not always possible to have access to gold-standard syntactic analyses. Therefore, in order to investigate how the quality of rules are affected by the quality of syntactic analysis, we conduct simulation experiments by varying the amount of gold-standard syntactically analysed training data. For each language, we sample x fully parsed sentences from the its treebank out of L training sentences available. For the remaining $L - x$ sentences, we use *silver* syntactic analysis i.e., we train a syntactic analysis model on x sentences and use the model predictions for the $L - x$ sentences.

Data and Setup: We experiment with Spanish, Greek, Belarusian and Lithuanian. For transfer learning, we use Portuguese, Ancient Greek, Ukrainian and Latvian treebanks respectively. The data statistics and details are in Appendix A.2.

We train `Udify` (Kondratyuk and Straka, 2019), a parser that jointly predict POS tags, morphological features, and dependency trees, using the x gold-standard sentences as our training data. We generate model predictions on the remaining $L - x$ sentences. Finally, we concatenate the x gold data with the $L - x$ automatically parsed data from which we extract the training data for learning the decision tree. We experiment with $x = [50, 100, 500]$ gold-standard sentences. To account of sampling randomness, we repeat the process 5 times and report averages across runs.

To further improve the quality of the automatically obtained syntactic analysis, we use cross-lingual transfer learning where we train the `Udify` model by concatenating x sentences of the target language with the entire treebank of the related

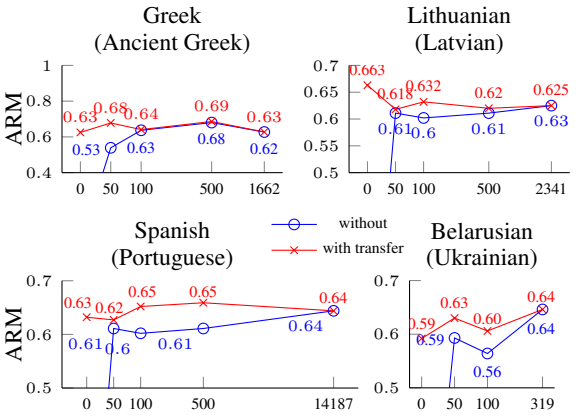

Figure 8: Comparing the (avg.) ARM score for `Number` agreement with and without cross-lingual transfer learning (transfer language in parenthesis). x-axis in log space. The higher the ARM the better.

[Relation, Head, Dependent]	correct label	gold	zero-shot
det, NOUN, DET.	almost always	required	required
mod, NOUN, ADJ	almost always	required	required
flat, PROPN, PROPN	almost always	required	chance
mod, PROPN, PROPN	almost always	required	chance
appos, PROPN, PROPN	sometimes	required	chance
comp:aux@pass, AUX, VERB	need not	chance	required
conj, PROPN, PROPN	need not	required	chance
ARM score over the test set:		0.644	0.632

Table 1: The Spanish gender rules extracted in a zero-shot setting are generally similar to the ones extracted from the gold data (93%). We highlight the few mistakes that the zero-shot tree makes.

language. We also conduct zero-shot experiments under this setting where we directly use the `Udify` model trained only on the related language and get the model predictions on L sentences. As before, we train five decision trees for each x setting and report the average ARM over the test data.

Results We report the results for Number agreement in Figure 8. Similar plots for other languages and features can be found in the Appendix A.5. We observe that using cross-lingual transfer learning (CLTL) already leads to high scores across all languages even in zero-shot settings where we do not use any data from the gold-standard treebank. Taking Spanish gender as an example, 93% of the rule-triples extracted from the gold-standard tree (which are overwhelmingly correct) are also extracted by the zero-shot tree. The zero-shot tree only makes a few mistakes (shown in Table 1 and reflected in its overall ARM score) on certain proper noun and auxiliary verb constructions. Interestingly, using CLTL, training with just 50 gold-standard target language sentences is almost equivalent to

training with 100 or 500 gold-standard sentences. This opens new avenues for language documentation: with as few as 50 expertly-annotated syntactic analysis of a new language and CLTL our framework can produce decent first-pass agreement rules. Needless to say, in most cases the extracted rules improve as we increase the number of gold-standard sentences and CLTL further helps bridge the data availability gap for low-resource settings.

5.2 Real Zero-Shot Experiments

Some languages like Breton, Buryat, Faroese, Tagalog and Welsh have test data only; there is no gold-standard training data available, which presents a *true* zero-shot setting. In such cases, we can still extract grammar rules with our framework using zero-shot dependency parsing.

Data and Setup: We collect raw text for the above languages from the Leipzig corpora (Goldhahn et al., 2012). Data statistics are listed in Appendix A.2. We parse these sentences using the "universal" `Udify` model that has been pre-trained on all of the UD treebanks, as released by (Kondratyuk and Straka, 2019). As before, we use these automatically parsed syntactic analyses to extract the rules which we evaluate with ARM over the gold standard test data of the corresponding SUD treebanks.

Results: We report the ARM scores in Figure 9. Averaged over all rules, our approach obtains a ARM of 0.566, while the naive all-chance baseline only achieves 0.506. The difference appears to be small, but we still consider it significant, because these languages do not actually require agreement for many grammatical features. Tagalog and Buryat are the most distant languages that we test on (no Philippine and Mongolic language is present in our training data) and yet we observe our method being at par with the baseline and even outperforming in case of Tagalog. Breton and Welsh, on the other hand, are an interesting test bed: Celtic languages are to some degree outliers among Indo-European languages (Borsley and Roberts, 2005), and we suspect that as a result the parser performs generally worse. Despite that, our approach has an ARM of 0.730 for Welsh gender agreement, as opposed to the mere 0.615 that the baseline achieves.

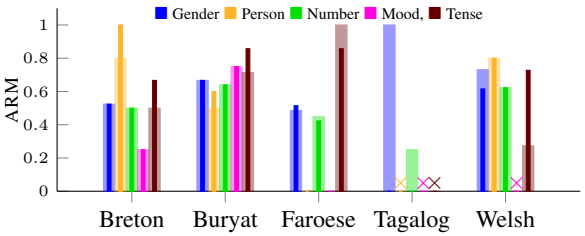

Figure 9: In most cases our framework (shaded bars) extracts a good first-pass specification for *true* zero-shot settings. Solid bars indicate the baseline.

6 Related Work

Bender et al. (2014) use interlinear glossed text (IGT) to extract lexical entities and morphological rules for an endangered language. They experiment with different systems which individually extract lemmas, lexical rules, word order and the case system, some of which use hand-specified rules. Howell et al. (2017) extend this to work to predict case system on additional languages. Zamaraeva (2016) also infer morphotactics from IGT using k-means clustering. To the best of our knowledge, our work is the first to propose a framework to extract first-pass grammatical agreement rules directly from raw text in a statistically-informed objective way. A parallel line of work (Hellan, 2010) extracts a *construction profile* of a language by having templates that define how sentences are constructed.

7 Future Work

While we have demonstrated that our approach is effective in extracting a first-pass set of agreement rules directly from raw text, it focuses only on agreement between a pair of words and hence might fail to capture more complex phenomena that require broader context or operate at the phrase level. Consider this simple English example: "John and Mary love their dog". Under both UD and SUD formalisms, the coordinating conjunction "and" is a dependent, hence the verb will not agree with either of the (singular) nouns ("John" or "Mary"). Also, deciding agreement based on only POS tags is insufficient to capture *all* phenomena that may influence agreement for e.g. mass nouns such as 'rice' do not follow the standard number agreement rules in English. We leave a more expressive model and evaluation on more languages as future work. We also plan to expand our methodology for extracting grammar rules from raw text to other aspects of morphosyntax, such as argument structure and word order phenomena.

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A Appendix

A.1 Decision Tree Hyperparameters

We perform a grid search over the following hyperparameters of the decision tree:

- `criterion` = [gini, entropy]
- `max depth` = [6,15]
- `min impurity decrease` = $1e^{-3}$

The best parameters are selected based on the validation set performance. For some treebanks which have no validation set we use the default cross-validation provided by `sklearn` (Buitinck et al., 2013). Average model runtime for a treebanks is 5-10mins depending on the size of the treebank.

A.2 Dataset Statistics

For the true low-resource experiments, the dataset details are in Table 2.

LANGUAGE	TRAIN / TEST
Breton-KEB	30000 / 888
Buryat-BXR	10000 / 908
Faroese-OFT	50000/ 1208
Tagalog-TRG	30000 / 55
Welsh-CCG	30000 / 956

Table 2: Dataset statistics. Training data is obtained by parsing the Liepzig corpora (Goldhahn et al., 2012) and test data is obtained from the respective treebank. Each cell denotes the number of sentences in train/test.

A.3 Evaluation

A.4 Annotation Interface for Expert Evaluation

In Figure 10, we show the annotation interface used for verifying `Gender` agreement rules in Catalan. For each triple, we display 10 randomly selected examples from the training portion of the treebank.

A.5 Low-resource Experiment Results

For the simulation experiments, the dataset details are in Table 3.

A.5.1 Udify (Kondratyuk and Straka, 2019) Model Details

We used the `Udify` model for automatically annotating the raw text with part-of-speech (POS), dependency links and morphological features. For each of the simulation experiment we report the `udify` parsing performance on the test data in Table 4. We used the same hyperparameters for training with a related languages as specified by the authors.[11]. In the configuration file, we only change the parameters `warmup steps`= 100 and `start-step`= 100, as recommended by the authors for low-resource languages.

A.5.2 Results and Discussion

For each language and feature, we plot the ARM score with and without transfer learning in Figure 12-14. Similar to our findings for `Gender` in Figure 5, we find that cross-lingual transfer leads to a better score across all languages in the zero-shot setting. As we increase the number of gold-standard sentences, the quality of extracted rules improve. Although, for Belarusian we observe the opposite trend for `Person` agreement. On closer inspection we find that it is because person applies only to non-past finite verb forms (VERB and AUX) as an inflectional feature and to pronouns (PRON) as a lexical feature which means that in many cases person is not explicitly marked, even though it implicitly exists [12].

A.6 Experiments with Gold-Standard Data

We present the ARM scores for all treebanks and features in Tables 5-11. We also report the validation results in the same tables for our best setting which uses the *Statistical Threshold*. In Section 2.2, we proposed using two types of thresholds for retaining the high probability agreement rules. In order to compare which threshold is the best for all treebanks, we manually inspect some of the learnt decision trees. We find that for the trees learnt from the *hard threshold* often over-fit on the training data causing to produce leaves with very few examples. In Figure 15 we compare the trees constructed for number agreement with the two thresholds for Marathi. One reason why *Statistical-Threshold* performs better for low-resource languages is because there are more leaves with fewer samples overall causing the *Hard Threshold* to have more false positives. Whereas the *Statistical Threshold* uses *effect size* with the significance test which takes into account the sample size within a leaf leading to better leaves. Therefore, we choose to use *Statistical-Threshold* for all our simulation experiments.

In Figure 11, we report that (avg.) number of leaves in the decision trees grouped by language

[11] https://github.com/Hyperparticle/udify

[12] https://universaldependencies.org/be/

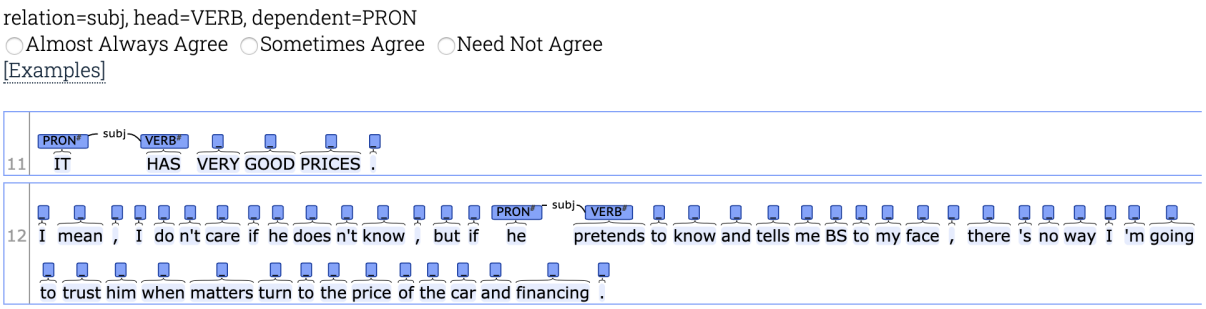


Figure 10: Annotation interface for evaluating `Gender` agreement in Catalan.

LANGUAGE	TRAIN/DEV/TEST	TRANSFER LANGUAGE
Spanish-GSD	14187 / 1400/ 426	Portuguese-Bosque
Greek-GDT	1662 / 403 / 456	Ancient Greek-PROIEL
Belarusian-HSE	319 / 65/ 253	Ukrainian-IU
Lithuanian-ALKSNIS	2341 / 617 / 684	Latvian-LVTB

Table 3: Dataset statistics. Train/Dev/Test denote the number of sentences in the respective treebank used for the target language.

family. Overall, `Gender` and `Case` tend to have more complex trees. For `Case`, it is probably because languages have more number of cases making it harder for the decision tree to model them.

A.7 SUD treebanks

Figure 16 presents a comparison of UD and SUD-style trees for the German sentence, “Ich werde lange Bücher lesen.". The SUD tree has the function word ‘werde’ as the syntactic head to the content word ‘lesen’.

LANGUAGE	#TRAINING	SETTING	
		W/O TRANSFER	+TRANSFER
Greek	0	-	upos:0.661, ufeats:0.392, uas:0.632, las :0.465
	50	upos:0.507, ufeats:0.330, uas:0.309, las:0.203	upos:0.877, ufeats:0.631, uas:0.724, las:0.653
	100	upos:0.915, ufeats:0.664, uas: 0.755, las: 0.691	upos: 0.906, ufeats: 0.719, uas: 0.758, las: 0.703
	500	upos: 0.970, ufeats: 0.891, uas: 0.891, las: 0.866	upos: 0.954, ufeats: 0.860, uas: 0.849, las: 0.817
Spanish	0	-	upos: 0.922, ufeats: 0.764, uas: 0.855, las: 0.776
	50	upos: 0.529, ufeats: 0.463, uas: 0.289, las: 0.152	upos: 0.913, ufeats: 0.792, , uas: 0.844, las: 0.767
	100	upos: 0.920, ufeats: 0.832, uas: 0.755, las: 0.690	upos: 0.916, ufeats: 0.840, uas: 0.849, las: 0.784
	500	upos: 0.952, ufeats: 0.919, uas: 0.860, las: 0.820	upos: 0.949, ufeats: 0.889, uas: 0.859, las: 0.822
Belarusian	0	-	upos: 0.941, ufeats: 0.520, uas: 0.863, las: 0.797
	50	upos: 0.570, ufeats: 0.323, uas: 0.217, las: 0.141	upos: 0.952, ufeats: 0.726, uas: 0.763, las: 0.727
	100	upos: 0.919, ufeats: 0.446, uas: 0.521, las: 0.482	upos: 0.961, ufeats: 0.777, uas: 0.854, las: 0.800
Lithuanian	0	-	upos: 0.869, ufeats: 0.528, uas: 0.752, las: 0.610
	50	upos: 0.566, ufeats: 0.371, uas: 0.346, las: 0.211	upos: 0.874, ufeats: 0.5841, uas: 0.757, las: 0.623
	100	upos: 0.813, ufeats: 0.453, uas: 0.551, las: 0.421	upos: 0.883, ufeats: 0.637, uas: 0.761, las: 0.659
	500	upos: 0.925, ufeats: 0.744, uas: 0.757, las: 0.697	upos: 0.912, ufeats: 0.747, uas: 0.779, las: 0.714

Table 4: `udify` model performance on the test data for each low-resource setting. The scores are averaged across five runs of each setting.

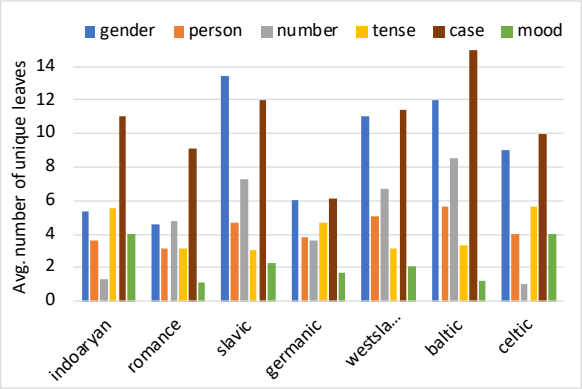


Figure 11: (Avg.) number of leaves for each feature grouped by language family.

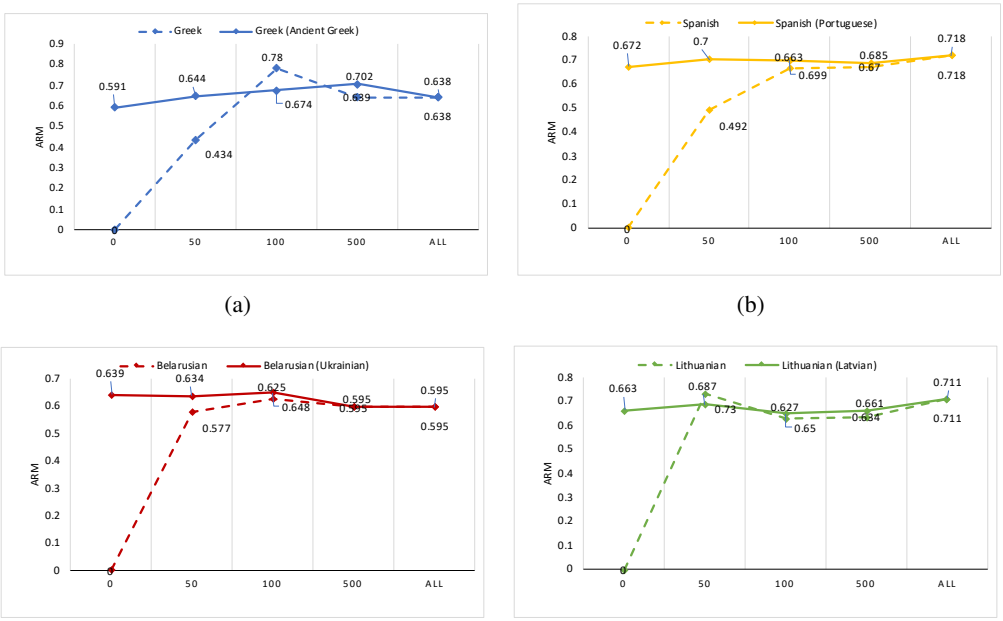


Figure 12: Comparing the (avg.) ARM score for `Gender` agreement with and without cross-lingual transfer learning (transfer language in parenthesis). Note: the higher the ARM the better.

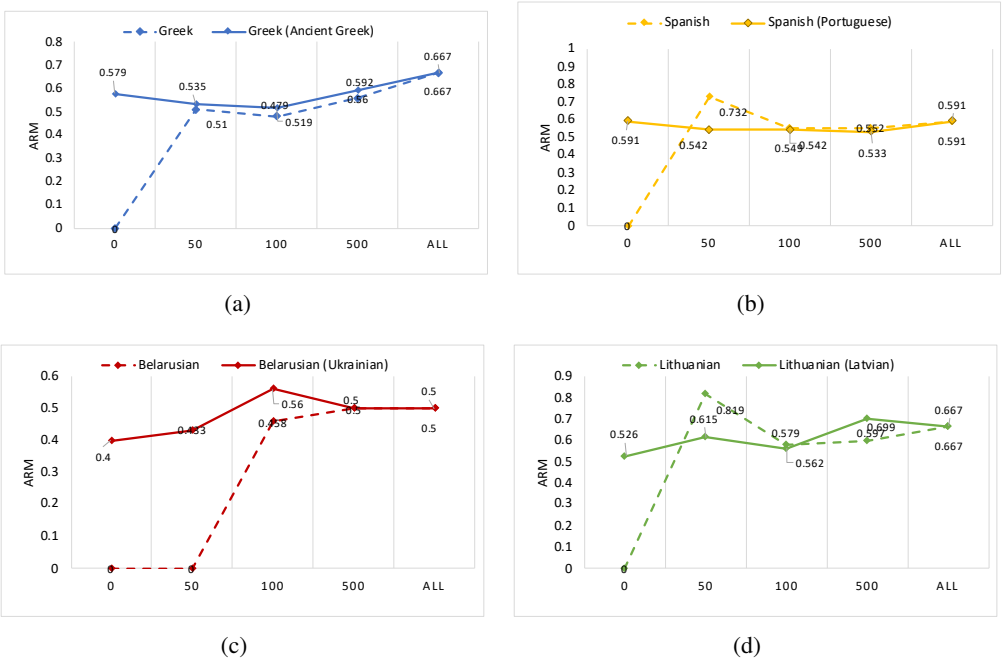


Figure 13: Comparing the (avg.) ARM score for `Person` agreement with and without cross-lingual transfer learning (transfer language in parenthesis). Note: the higher the ARM the better.

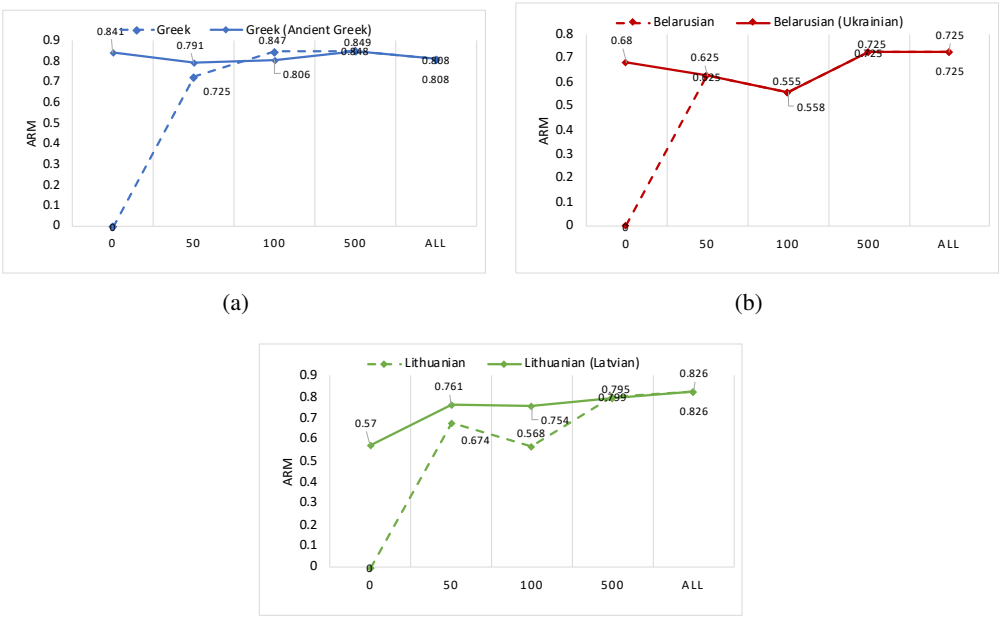
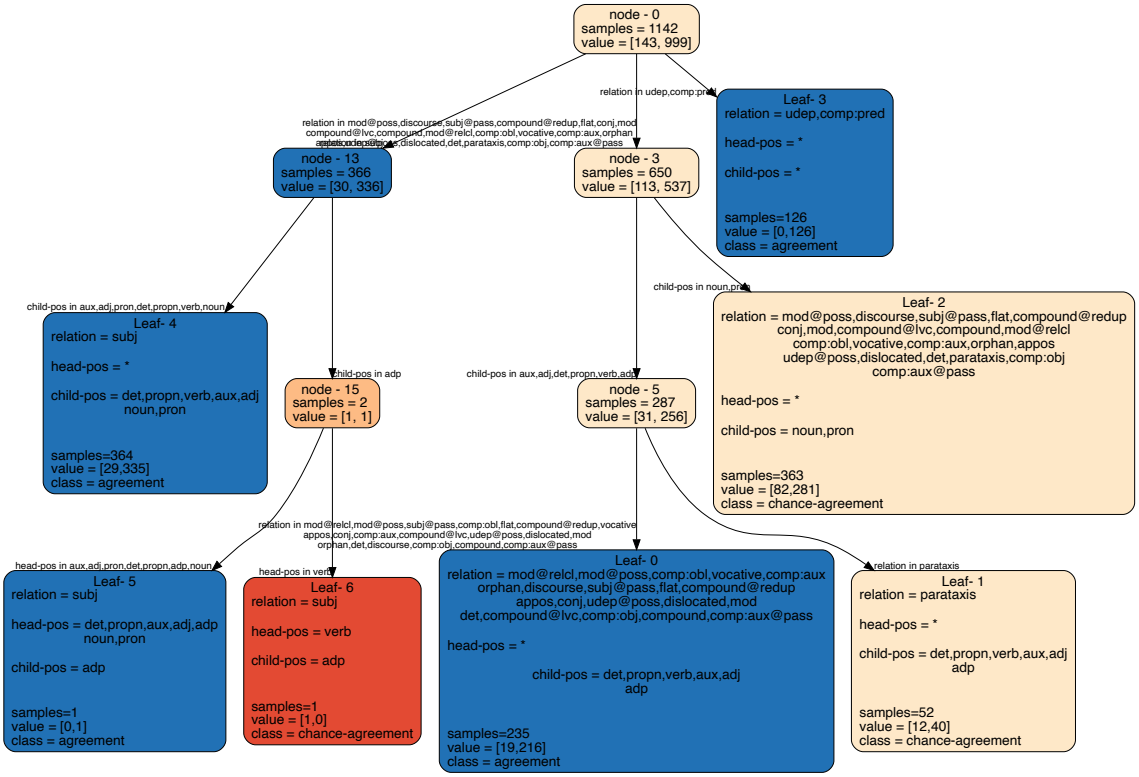
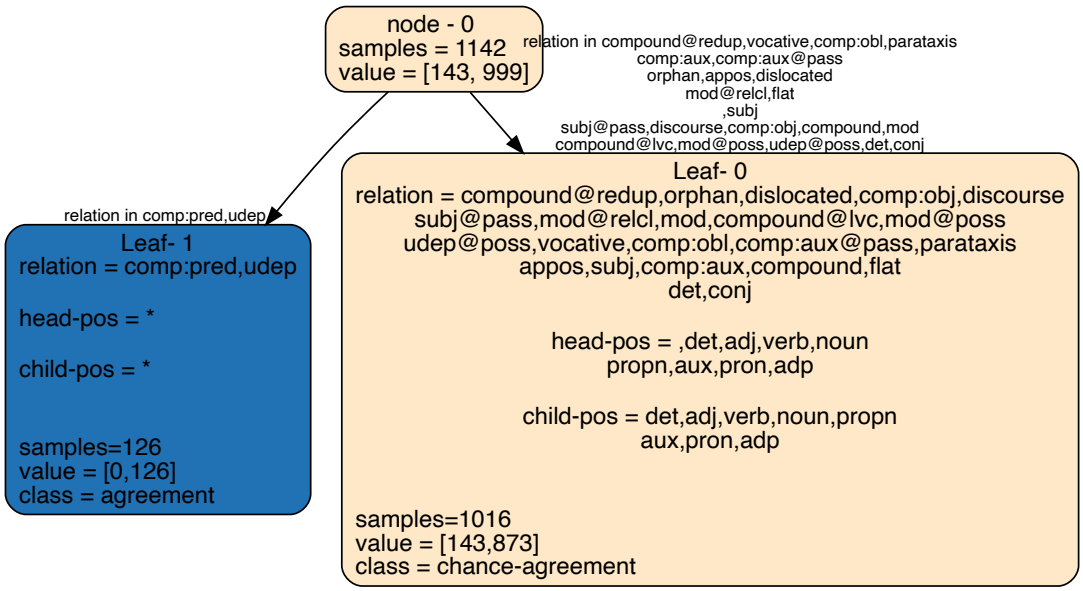


Figure 14: Comparing the (avg.) ARM score for `Case` agreement with and without cross-lingual transfer learning (transfer language in parenthesis). Note: the higher the ARM the better. For Spanish, there was < 10 data points with `Case` annotated hence we do not report results for it.



(a)



(b)

Figure 15: Comparing the learnt trees for `Number` agreement extracted using (a) *Hard Threshold* and (b) *Statistical Threshold*. *Hard Threshold* overfits on the training data resulting in leaves with very few samples.

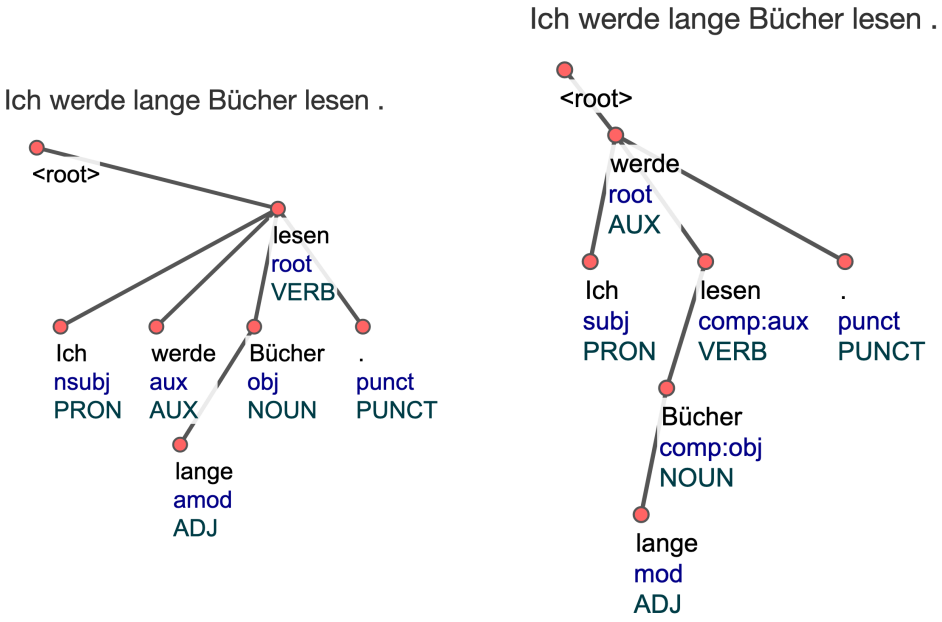


Figure 16: Comparing the UD (a) tree with the SUD (b) tree for the German sentence “Ich werde lange Bücher lesen.".

TREEBANK	FEATURE	STATISTICAL	HARD	BASELINE	DEV
ru-gsd	Gender	0.678	-	0.51	0.623
ru-gsd	Person	0.125	0.875	0.125	0.286
ru-gsd	Number	0.628	0.512	0.384	0.62
ru-gsd	Tense	0.667	0.667	0.667	0.571
ru-gsd	Mood	0.0	1.0	0.0	0.1
ru-gsd	Case	0.649	0.614	0.395	0.537
id-gsd	Number	0.047	0.961	0.047	0.045
it-isdt	Gender	0.816	0.816	0.289	0.738
it-isdt	Person	0.304	0.87	0.304	0.619
it-isdt	Number	0.615	0.603	0.41	0.588
it-isdt	Tense	0.765	0.765	0.647	0.611
it-isdt	Mood	0.25	0.75	0.25	0.273
la-proiel	Gender	0.538	0.568	0.636	0.496
la-proiel	Person	0.56	0.6	0.54	0.653
la-proiel	Number	0.648	0.574	0.452	0.553
la-proiel	Tense	0.818	0.879	0.879	0.824
la-proiel	Mood	0.6	0.52	0.44	0.667
la-proiel	Case	0.759	0.782	0.466	0.691
ro-nonstandard	Gender	0.64	0.57	0.407	0.75
ro-nonstandard	Person	0.636	0.606	0.606	0.683
ro-nonstandard	Number	0.626	0.626	0.586	0.693
ro-nonstandard	Tense	0.452	0.839	0.645	0.467
ro-nonstandard	Mood	0.676	0.765	0.676	0.4
ro-nonstandard	Case	0.694	0.702	0.636	0.704
he-htb	Gender	0.747	0.747	0.663	0.629
he-htb	Person	0.737	0.789	0.789	0.769
he-htb	Number	0.585	0.585	0.415	0.505
he-htb	Tense	0.3	0.3	0.1	0.545
he-htb	Case	0.5	0.5	0.0	0.5
no-bokmaal	Gender	0.477	0.568	0.545	0.675
no-bokmaal	Person	1.0	1.0	0.5	1.0
no-bokmaal	Number	0.655	0.673	0.364	0.733
no-bokmaal	Tense	0.55	0.55	0.55	0.55
no-bokmaal	Mood	0.0	1.0	0.0	0.1
no-bokmaal	Case	0.0	0.333	0.0	0.0
no-nynorsk	Gender	0.464	0.536	0.536	0.514
no-nynorsk	Person	0.0	0.0	0.0	0.667
no-nynorsk	Number	0.702	0.702	0.511	0.596
no-nynorsk	Tense	0.368	0.368	0.684	0.429
no-nynorsk	Mood	0.0	1.0	0.0	0.048
fi-tdt	Person	0.387	0.677	0.677	0.607
fi-tdt	Number	0.502	0.493	0.511	0.559
fi-tdt	Tense	0.474	0.368	0.474	0.5
fi-tdt	Mood	0.75	0.75	0.75	0.471
fi-tdt	Case	0.786	0.828	0.821	0.781
pl-lfg	Gender	0.646	0.646	0.463	0.641
pl-lfg	Person	0.688	0.688	0.562	0.714
pl-lfg	Number	0.691	0.68	0.412	0.624
pl-lfg	Tense	0.556	0.667	0.667	0.6
pl-lfg	Mood	0.333	0.667	0.333	0.4
pl-lfg	Case	0.744	0.667	0.41	0.617
grc-perseus	Gender	0.62	0.718	0.563	0.699
grc-perseus	Person	0.8	0.8	0.7	0.636
grc-perseus	Number	0.531	0.63	0.605	0.537
grc-perseus	Tense	0.889	1.0	1.0	0.778
grc-perseus	Mood	0.833	0.833	0.667	0.429
grc-perseus	Case	0.708	0.792	0.556	0.712
fi-ftb	Person	0.56	0.76	0.6	0.63
fi-ftb	Number	0.524	0.441	0.524	0.54
fi-ftb	Tense	0.846	0.769	0.308	0.538
fi-ftb	Mood	0.429	0.5	0.429	0.529
fi-ftb	Case	0.724	0.848	0.781	0.748
wo-wtb	Gender	0.5	0.5	0.5	0.0
wo-wtb	Person	0.55	0.45	0.4	0.609
wo-wtb	Number	0.486	0.6	0.6	0.632
wo-wtb	Tense	0.5	0.625	0.375	0.625
wo-wtb	Mood	0.143	0.143	0.143	0.364
en-partut	Person	0.5	0.5	0.417	0.857
en-partut	Number	0.559	0.559	0.441	0.676
en-partut	Tense	0.667	0.733	0.667	0.583
en-partut	Mood	0.091	0.818	0.091	0.1

Table 5: Comparing the ARM scores for SUD treebanks across both Statistical and Hard thresholding.

TREEBANK	FEATURE	STATISTICAL	HARD	BASELINE	DEV
fr-ftb	Gender	0.631	0.631	0.477	0.621
fr-ftb	Person	0.14	0.86	0.14	0.171
fr-ftb	Number	0.635	0.635	0.502	0.634
fr-ftb	Tense	0.714	0.857	0.857	0.833
fr-ftb	Mood	0.409	0.591	0.409	0.6
lv-lvtb	Gender	0.727	0.734	0.461	0.677
lv-lvtb	Person	0.5	0.632	0.579	0.583
lv-lvtb	Number	0.688	0.688	0.429	0.706
lv-lvtb	Tense	0.667	0.815	0.889	0.741
lv-lvtb	Mood	0.476	0.619	0.476	0.333
lv-lvtb	Case	0.719	0.734	0.489	0.772
ro-rrt	Gender	0.583	0.583	0.51	0.591
ro-rrt	Person	0.327	0.755	0.347	0.304
ro-rrt	Number	0.535	0.585	0.528	0.56
ro-rrt	Tense	0.421	0.684	0.789	0.526
ro-rrt	Mood	0.931	1.0	0.448	0.867
ro-rrt	Case	0.862	0.788	0.588	0.854
it-vit	Gender	0.672	0.672	0.375	0.678
it-vit	Person	0.625	0.625	0.792	0.667
it-vit	Number	0.712	0.728	0.528	0.61
it-vit	Tense	0.773	0.955	0.955	0.75
it-vit	Mood	0.4	0.6	0.4	0.231
fr-partut	Gender	0.579	0.632	0.421	0.615
fr-partut	Person	0.818	0.727	0.273	0.75
fr-partut	Number	0.771	0.542	0.292	0.542
fr-partut	Tense	0.857	0.857	0.714	0.6
fr-partut	Mood	0.333	0.667	0.333	0.167
en-ewt	Person	0.812	0.812	0.25	0.85
en-ewt	Number	0.357	0.643	0.357	0.304
en-ewt	Tense	0.591	0.773	0.773	0.593
en-ewt	Mood	0.4	0.733	0.4	0.333
ru-syntagrus	Gender	0.697	0.747	0.624	0.673
ru-syntagrus	Person	0.625	0.667	0.667	0.72
ru-syntagrus	Number	0.591	0.661	0.562	0.576
ru-syntagrus	Tense	0.727	0.818	0.818	0.667
ru-syntagrus	Mood	0.4	0.8	0.44	0.407
ru-syntagrus	Case	0.649	0.707	0.575	0.681
sv-talbanken	Gender	0.719	0.719	0.438	0.643
sv-talbanken	Number	0.659	0.634	0.463	0.571
sv-talbanken	Tense	0.559	0.588	0.5	0.607
sv-talbanken	Mood	0.048	0.952	0.048	0.056
sv-talbanken	Case	0.189	0.623	0.189	0.143
olo-kkpp	Person	0.286	0.571	0.286	-
olo-kkpp	Number	0.667	0.692	0.667	-
olo-kkpp	Tense	0.75	0.75	0.75	-
olo-kkpp	Mood	0.0	0.75	0.0	-
olo-kkpp	Case	0.7	0.7	0.7	-
cs-cac	Gender	0.663	0.673	0.602	0.678
cs-cac	Person	0.562	0.562	0.5	0.583
cs-cac	Number	0.636	0.531	0.469	0.575
cs-cac	Tense	0.467	0.667	0.6	0.333
cs-cac	Mood	0.2	0.4	0.2	0.111
cs-cac	Case	0.81	0.84	0.46	0.833
ur-udtb	Gender	0.567	0.567	0.536	0.576
ur-udtb	Person	0.152	0.946	0.065	0.195
ur-udtb	Number	0.485	0.583	0.485	0.496
ur-udtb	Tense	0.333	0.5	0.5	0.667
ur-udtb	Mood	0.714	0.714	0.143	0.714
ur-udtb	Case	0.685	0.696	0.696	0.7
et-ewt	Person	0.609	0.696	0.609	-
et-ewt	Number	0.551	0.551	0.48	-
et-ewt	Tense	0.409	0.682	0.636	-
et-ewt	Mood	0.533	0.4	0.533	-
et-ewt	Case	0.7	0.754	0.657	-
fro-srcmf	Tense	0.5	1.0	0.5	1.0
es-gsd	Gender	0.718	0.718	0.366	0.736
es-gsd	Person	0.591	0.545	0.591	0.355
es-gsd	Number	0.644	0.644	0.424	0.567
es-gsd	Tense	0.529	0.824	0.824	0.409
es-gsd	Mood	0.533	0.467	0.533	0.474
es-gsd	Case	0.0	1.0	0.0	0.0

Table 6: Comparing the ARM scores for SUD treebanks across both Statistical and Hard thresholding.

TREEBANK	FEATURE	STATISTICAL	HARD	BASELINE	DEV
sl-ssj	Gender	0.818	0.8	0.527	0.772
sl-ssj	Person	0.667	0.722	0.722	0.706
sl-ssj	Number	0.683	0.683	0.564	0.712
sl-ssj	Tense	0.333	0.583	0.333	0.364
sl-ssj	Mood	0.5	0.75	0.5	0.667
sl-ssj	Case	0.607	0.721	0.557	0.61
cs-pdt	Gender	0.564	0.788	0.75	0.58
cs-pdt	Person	0.591	0.705	0.614	0.541
cs-pdt	Number	0.477	0.64	0.629	0.481
cs-pdt	Tense	0.667	0.786	0.786	0.658
cs-pdt	Mood	0.538	0.538	0.538	0.48
cs-pdt	Case	0.646	0.675	0.545	0.633
hsb-ufal	Gender	0.857	0.714	0.786	-
hsb-ufal	Number	0.692	0.538	0.692	-
hsb-ufal	Tense	0.667	0.667	0.667	-
hsb-ufal	Case	1.0	0.846	0.462	-
ga-idt	Gender	0.64	0.76	0.78	0.647
ga-idt	Person	0.625	0.875	0.5	1.0
ga-idt	Number	0.468	0.571	0.468	0.446
ga-idt	Tense	0.714	0.571	0.429	0.5
ga-idt	Mood	0.833	0.833	0.667	0.714
ga-idt	Case	0.69	0.724	0.724	0.667
gl-treegal	Gender	0.722	0.685	0.333	-
gl-treegal	Person	0.522	0.565	0.522	-
gl-treegal	Number	0.68	0.546	0.361	-
gl-treegal	Tense	0.462	0.538	0.692	-
gl-treegal	Mood	0.462	0.692	0.462	-
fa-seraji	Person	0.667	0.667	0.381	0.842
fa-seraji	Number	0.514	0.514	0.514	0.556
fa-seraji	Tense	0.455	0.545	0.636	0.545
fa-seraji	Mood	0.333	0.667	0.333	0.0
et-edt	Person	0.613	0.613	0.71	0.714
et-edt	Number	0.648	0.644	0.539	0.676
et-edt	Tense	0.579	0.632	0.763	0.537
et-edt	Mood	0.524	0.571	0.571	0.667
et-edt	Case	0.565	0.756	0.786	0.614
la-perseus	Gender	0.692	0.585	0.538	-
la-perseus	Person	0.5	0.667	0.833	-
la-perseus	Number	0.544	0.662	0.603	-
la-perseus	Tense	0.75	1.0	1.0	-
la-perseus	Mood	0.667	0.667	0.833	-
la-perseus	Case	0.717	0.66	0.528	-
ug-udt	Person	0.526	0.526	0.579	0.611
ug-udt	Number	0.767	0.6	0.533	0.697
ug-udt	Tense	0.625	0.75	0.5	0.778
ug-udt	Mood	0.692	0.923	0.769	0.833
ug-udt	Case	0.683	0.683	0.683	0.671
es-ancora	Gender	0.754	0.754	0.431	0.759
es-ancora	Person	0.429	0.429	0.429	0.526
es-ancora	Number	0.664	0.664	0.539	0.651
es-ancora	Tense	0.625	0.833	0.833	0.63
es-ancora	Mood	0.652	0.348	0.652	0.5
de-hdt	Gender	0.541	0.607	0.607	0.603
de-hdt	Person	0.071	0.929	0.071	0.085
de-hdt	Number	0.561	0.595	0.59	0.533
de-hdt	Tense	0.8	0.88	0.88	0.692
de-hdt	Mood	0.0	1.0	0.0	0.077
de-hdt	Case	0.738	0.836	0.574	0.7
kk-ktb	Person	0.636	0.545	0.636	-
kk-ktb	Number	0.538	0.615	0.538	-
kk-ktb	Mood	1.0	1.0	0.6	-
de-gsd	Gender	0.699	0.781	0.397	0.641
de-gsd	Person	0.567	0.433	0.567	0.667
de-gsd	Number	0.638	0.638	0.35	0.619
de-gsd	Tense	0.455	0.636	0.591	0.526
de-gsd	Mood	0.5	0.455	0.455	0.421
de-gsd	Case	0.55	0.588	0.362	0.603
nl-alpino	Gender	0.667	0.8	0.8	0.562
nl-alpino	Number	0.548	0.548	0.565	0.625
nl-alpino	Tense	0.562	0.5	0.375	0.529
af-afribooms	Number	0.6	0.667	0.533	0.667
af-afribooms	Tense	0.842	0.842	0.842	0.588
af-afribooms	Case	0.0	1.0	0.0	0.0

Table 7: Comparing the ARM scores for SUD treebanks across both Statistical and Hard thresholding.

TREEBANK	FEATURE	STATISTICAL	HARD	BASELINE	DEV
uk-iu	Gender	0.701	0.693	0.559	0.771
uk-iu	Person	0.7	0.5	0.35	0.9
uk-iu	Number	0.647	0.659	0.479	0.656
uk-iu	Tense	0.476	0.476	0.571	0.615
uk-iu	Mood	0.318	0.409	0.318	0.357
uk-iu	Case	0.741	0.741	0.504	0.732
cs-cltt	Gender	0.857	0.929	0.75	0.806
cs-cltt	Number	0.646	0.688	0.479	0.576
cs-cltt	Tense	0.167	0.5	0.167	0.143
cs-cltt	Mood	0.0	1.0	0.0	0.0
cs-cltt	Case	0.697	0.758	0.636	0.658
cop-scriptorium	Gender	0.714	0.857	0.143	0.8
cop-scriptorium	Number	0.4	0.6	0.2	0.714
ru-taiga	Gender	0.648	0.724	0.638	0.667
ru-taiga	Person	0.667	0.75	0.583	0.786
ru-taiga	Number	0.662	0.601	0.459	0.646
ru-taiga	Tense	0.538	0.615	0.615	0.583
ru-taiga	Mood	0.611	0.667	0.611	0.5
ru-taiga	Case	0.557	0.696	0.633	0.593
hu-szeged	Person	0.444	0.556	0.444	0.138
hu-szeged	Number	0.396	0.64	0.396	0.434
hu-szeged	Tense	0.6	0.8	0.8	0.769
hu-szeged	Mood	0.714	0.714	0.714	0.5
sr-set	Gender	0.803	0.817	0.479	0.622
sr-set	Person	0.35	0.75	0.35	0.4
sr-set	Number	0.64	0.64	0.509	0.615
sr-set	Tense	0.474	0.684	0.684	0.444
sr-set	Mood	0.286	0.714	0.286	0.2
sr-set	Case	0.704	0.765	0.531	0.651
en-lines	Person	0.625	0.688	0.562	0.789
en-lines	Number	0.319	0.783	0.319	0.325
en-lines	Tense	0.704	0.778	0.704	0.636
en-lines	Mood	0.211	0.789	0.211	0.207
en-lines	Case	0.778	0.778	0.444	0.833
sk-snk	Gender	0.692	0.776	0.533	0.638
sk-snk	Person	0.778	0.333	0.222	0.625
sk-snk	Number	0.558	0.558	0.5	0.571
sk-snk	Tense	0.667	0.556	0.444	0.8
sk-snk	Mood	1.0	1.0	0.25	0.857
sk-snk	Case	0.731	0.756	0.526	0.833
pl-pdb	Gender	0.645	0.779	0.529	0.661
pl-pdb	Person	0.556	0.778	0.704	0.72
pl-pdb	Number	0.637	0.613	0.481	0.644
pl-pdb	Tense	0.5	0.6	0.7	0.6
pl-pdb	Mood	0.25	0.75	0.25	0.05
pl-pdb	Case	0.72	0.748	0.514	0.679
la-ittb	Gender	0.735	0.725	0.48	0.805
la-ittb	Person	0.19	0.81	0.19	0.273
la-ittb	Number	0.579	0.579	0.386	0.562
la-ittb	Tense	0.5	0.6	0.6	0.414
la-ittb	Mood	0.476	0.476	0.571	0.591
la-ittb	Case	0.757	0.796	0.495	0.792

Table 8: Comparing the ARM scores for SUD treebanks across both Statistical and Hard thresholding.

TREEBANK	FEATURE	STATISTICAL	HARD	BASELINE	DEV
da-ddt	Gender	0.818	0.818	0.364	0.889
da-ddt	Number	0.667	0.667	0.286	0.725
da-ddt	Tense	0.737	0.737	0.842	0.562
da-ddt	Mood	0.2	0.8	0.2	0.077
it-postwita	Gender	0.702	0.702	0.362	0.674
it-postwita	Person	0.595	0.676	0.73	0.595
it-postwita	Number	0.744	0.744	0.558	0.642
it-postwita	Tense	0.481	0.704	0.704	0.607
it-postwita	Mood	0.792	0.792	0.792	0.556
eu-bdt	Number	0.508	0.6	0.415	0.473
eu-bdt	Mood	0.421	0.737	0.421	0.529
eu-bdt	Case	0.795	0.803	0.726	0.776
sl-sst	Gender	0.724	0.618	0.513	-
sl-sst	Person	0.688	0.812	0.719	-
sl-sst	Number	0.678	0.672	0.483	-
sl-sst	Tense	0.48	0.76	0.48	-
sl-sst	Mood	0.56	0.6	0.56	-
sl-sst	Case	0.615	0.637	0.549	-
be-hse	Gender	0.596	0.553	0.404	0.692
be-hse	Person	0.5	0.5	0.0	0.75
be-hse	Number	0.646	0.646	0.431	0.596
be-hse	Tense	0.429	0.429	0.571	0.333
be-hse	Mood	0.286	0.286	0.286	0.2
be-hse	Case	0.725	0.55	0.45	0.733
fr-sequoia	Gender	0.8	0.771	0.371	0.647
fr-sequoia	Person	0.667	0.667	0.4	0.857
fr-sequoia	Number	0.56	0.62	0.45	0.68
fr-sequoia	Tense	0.529	0.765	0.765	0.684
fr-sequoia	Mood	0.286	0.714	0.286	0.077
sme-giella	Number	0.653	0.653	0.561	-
sme-giella	Tense	0.455	0.545	0.455	-
sme-giella	Mood	0.214	0.571	0.214	-
sme-giella	Case	0.741	0.704	0.667	-
el-gdt	Gender	0.638	0.745	0.447	0.744
el-gdt	Person	0.667	0.667	0.458	0.667
el-gdt	Number	0.627	0.7	0.427	0.615
el-gdt	Tense	0.6	1.0	1.0	0.462
el-gdt	Mood	0.0	1.0	0.0	0.0
el-gdt	Case	0.809	0.809	0.319	0.814
orv-torot	Gender	0.655	0.669	0.547	0.679
orv-torot	Person	0.6	0.6	0.6	0.594
orv-torot	Number	0.621	0.621	0.581	0.618
orv-torot	Tense	0.731	0.731	0.769	0.72
orv-torot	Mood	0.316	0.789	0.421	0.176
orv-torot	Case	0.709	0.775	0.609	0.691
sv-lines	Gender	0.538	0.538	0.308	0.64
sv-lines	Number	0.643	0.643	0.452	0.529
sv-lines	Tense	0.429	0.476	0.429	0.655
sv-lines	Mood	0.231	0.769	0.231	0.161
sv-lines	Case	0.583	0.583	0.25	0.51
ta-ttb	Gender	0.682	0.682	0.659	0.5
ta-ttb	Person	0.091	0.955	0.091	0.167
ta-ttb	Number	0.523	0.591	0.545	0.533
ta-ttb	Tense	0.625	0.5	0.625	0.667
ta-ttb	Mood	0.5	1.0	0.5	0.5
ta-ttb	Case	0.846	0.846	0.692	1.0
it-partut	Gender	0.786	0.786	0.25	0.846
it-partut	Person	0.833	0.917	0.25	0.615
it-partut	Number	0.714	0.508	0.286	0.576
it-partut	Tense	0.9	0.9	0.6	0.583
it-partut	Mood	0.2	0.4	0.2	0.167
ar-padt	Gender	0.592	0.592	0.549	0.712
ar-padt	Person	0.0	0.833	0.0	0.263
ar-padt	Number	0.512	0.643	0.512	0.593
ar-padt	Mood	0.571	0.571	0.571	0.6
ar-padt	Case	0.871	0.871	0.753	0.824
bg-btb	Gender	0.638	0.66	0.404	0.585
bg-btb	Person	0.625	0.625	0.625	0.625
bg-btb	Number	0.639	0.631	0.533	0.679
bg-btb	Tense	0.6	0.6	0.6	0.579
bg-btb	Mood	0.056	0.944	0.056	0.176

Table 9: Comparing the ARM scores for SUD treebanks across both Statistical and Hard thresholding.

TREEBANK	FEATURE	STATISTICAL	HARD	BASELINE	DEV
pt-bosque	Gender	0.656	0.721	0.41	0.792
pt-bosque	Person	0.25	0.75	0.25	0.455
pt-bosque	Number	0.669	0.669	0.378	0.698
pt-bosque	Tense	0.5	0.438	0.438	0.692
pt-bosque	Mood	0.375	0.5	0.375	0.429
lt-alksnis	Gender	0.711	0.711	-	0.671
lt-alksnis	Person	0.667	0.8	0.667	0.571
lt-alksnis	Number	0.625	0.625	0.531	0.595
lt-alksnis	Tense	0.667	0.667	0.667	0.6
lt-alksnis	Mood	0.667	0.333	0.667	0.375
lt-alksnis	Case	0.826	0.826	0.496	0.798
ar-nyuad	Gender	0.606	0.718	0.718	0.536
ar-nyuad	Person	0.469	0.562	0.469	0.343
ar-nyuad	Number	0.502	0.554	0.502	0.468
ar-nyuad	Mood	0.438	0.562	0.438	0.5
ar-nyuad	Case	0.627	0.747	0.747	0.551
ca-ancora	Gender	0.804	0.786	0.464	0.77
ca-ancora	Person	0.389	0.611	0.389	0.219
ca-ancora	Number	0.652	0.652	0.511	0.616
ca-ancora	Tense	0.5	0.731	0.692	0.56
ca-ancora	Mood	0.32	0.68	0.32	0.348
grc-proiel	Gender	0.605	0.516	0.535	0.588
grc-proiel	Person	0.543	0.543	0.6	0.737
grc-proiel	Number	0.533	0.61	0.538	0.585
grc-proiel	Tense	0.643	0.786	0.786	0.774
grc-proiel	Mood	0.529	0.529	0.529	0.65
grc-proiel	Case	0.809	0.854	0.51	0.813
it-twittiro	Gender	0.808	0.808	0.385	0.65
it-twittiro	Person	0.591	0.318	0.682	0.579
it-twittiro	Number	0.568	0.568	0.419	0.634
it-twittiro	Tense	0.25	0.75	0.75	0.462
it-twittiro	Mood	0.5	0.5	0.5	0.364
mr-ufal	Gender	0.609	0.652	0.565	0.52
mr-ufal	Person	0.727	0.727	0.364	0.889
mr-ufal	Number	0.394	0.794	0.242	0.514
mr-ufal	Case	0.583	0.583	0.417	0.857
tr-imst	Person	0.359	0.818	0.359	0.342
tr-imst	Number	0.47	0.536	0.47	0.485
tr-imst	Tense	0.762	0.762	0.81	0.68
tr-imst	Mood	0.714	0.714	0.714	0.68
tr-imst	Case	0.717	0.804	0.804	0.678
bxr-bdt	Case	0.818	0.545	0.818	-
hi-hdtb	Gender	0.586	0.617	0.5	0.631
hi-hdtb	Person	0.045	0.955	0.045	0.052
hi-hdtb	Number	0.416	0.615	0.416	0.455
hi-hdtb	Tense	0.333	0.333	0.333	0.2
hi-hdtb	Mood	1.0	1.0	0.333	0.667
hi-hdtb	Case	0.654	0.709	0.63	0.62
hr-set	Gender	0.725	0.717	0.525	0.643
hr-set	Person	0.769	0.769	0.577	0.692
hr-set	Number	0.675	0.675	0.51	0.658
hr-set	Tense	0.429	0.714	0.714	0.542
hr-set	Mood	0.412	0.588	0.412	0.158
hr-set	Case	0.669	0.725	0.577	0.659
kmr-mg	Gender	1.0	0.818	1.0	-
kmr-mg	Number	0.783	0.739	0.783	-
kmr-mg	Case	0.909	0.727	0.909	-
nl-lassysmall	Gender	0.85	0.85	0.9	0.81
nl-lassysmall	Number	0.646	0.646	0.523	0.646
nl-lassysmall	Tense	0.6	0.6	0.4	0.364
fr-gsd	Gender	0.727	0.727	0.485	0.807
fr-gsd	Person	0.375	0.719	0.375	0.312
fr-gsd	Number	0.624	0.624	0.441	0.593
fr-gsd	Tense	0.706	0.706	0.765	0.81
fr-gsd	Mood	0.273	0.727	0.273	0.25

Table 10: Comparing the ARM scores for SUD treebanks across both Statistical and Hard thresholding.

TREEBANK	FEATURE	STATISTICAL	HARD	BASELINE	DEV
got-proiel	Gender	0.559	0.595	0.559	0.658
got-proiel	Person	0.571	0.771	0.657	0.614
got-proiel	Number	0.64	0.68	0.503	0.591
got-proiel	Tense	0.714	0.714	0.714	0.586
got-proiel	Mood	0.722	0.722	0.611	0.682
got-proiel	Case	0.82	0.784	0.505	0.803
en-gum	Person	0.167	0.917	0.167	0.176
en-gum	Number	0.397	0.767	0.397	0.259
en-gum	Tense	0.579	0.684	0.579	0.625
en-gum	Mood	0.176	0.824	0.176	0.05
lzh-kyoto	Mood	0.0	1.0	0.0	0.0
lzh-kyoto	Case	0.0	1.0	0.0	0.125
cs-fictree	Gender	0.717	0.683	0.4	0.691
cs-fictree	Person	0.667	0.905	0.81	0.625
cs-fictree	Number	0.649	0.649	0.364	0.673
cs-fictree	Tense	0.833	0.889	0.778	0.565
cs-fictree	Mood	0.455	0.455	0.545	0.643
cs-fictree	Case	0.697	0.652	0.461	0.738
hy-armtdp	Person	0.444	0.593	0.593	0.692
hy-armtdp	Number	0.592	0.612	0.561	0.676
hy-armtdp	Tense	0.824	0.765	0.529	0.733
hy-armtdp	Mood	0.789	0.789	0.737	0.8
hy-armtdp	Case	0.857	0.857	0.821	0.772
gd-arcosg	Gender	0.615	0.615	0.615	0.609
gd-arcosg	Person	0.6	0.8	0.6	0.75
gd-arcosg	Number	0.562	0.562	0.562	0.588
gd-arcosg	Tense	0.833	0.333	0.5	0.8
gd-arcosg	Mood	0.667	0.667	0.333	0.714
gd-arcosg	Case	0.85	0.85	0.5	0.833
lt-hse	Gender	0.658	0.553	0.474	0.6
lt-hse	Person	0.778	0.444	0.444	0.8
lt-hse	Number	0.642	0.597	0.478	0.667
lt-hse	Tense	0.714	0.857	0.857	0.889
lt-hse	Mood	0.2	0.6	0.2	0.429
lt-hse	Case	0.564	0.615	0.641	0.816
no-nynorsklia	Gender	0.727	0.697	0.455	0.667
no-nynorsklia	Person	1.0	1.0	0.0	1.0
no-nynorsklia	Number	0.743	0.743	0.343	0.649
no-nynorsklia	Tense	0.435	0.826	0.783	0.435
no-nynorsklia	Mood	0.0	1.0	0.0	0.043
no-nynorsklia	Case	0.5	1.0	0.5	0.0
cu-proiel	Gender	0.61	0.66	0.54	0.706
cu-proiel	Person	0.667	0.667	0.528	0.579
cu-proiel	Number	0.672	0.579	0.503	0.641
cu-proiel	Tense	0.567	0.533	0.6	0.655
cu-proiel	Mood	0.348	0.652	0.348	0.364
cu-proiel	Case	0.818	0.818	0.473	0.793

Table 11: Comparing the ARM scores for SUD treebanks across both Statistical and Hard thresholding.