

Linguistic Typology Features from Text: Inferring the Sparse Features of World Atlas of Language Structures

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Abstract

The use of linguistic typological resources in natural language processing has been steadily gaining more popularity. It has been observed that the use of typological information, often combined with distributed language representations, leads to significantly more powerful models. While linguistic typology representations from various resources have mostly been used for conditioning the models, there has been relatively little attention on predicting features from these resources from the input data. In this paper we investigate whether the various linguistic features from World Atlas of Language Structures (WALS) can be reliably inferred from multi-lingual text. Such a predictor can be used to infer structural features for a language never observed in training data. We frame this task as a multi-label classification involving predicting the set of non-mutually exclusive and extremely sparse multi-valued labels (WALS features). We construct a recurrent neural network predictor based on byte embeddings and convolutional layers and test its performance on 556 languages, providing analysis for various linguistic types, macro-areas, language families and individual features. We show that some features from various linguistic types can be predicted reliably.

Note from the authors (April, 2020): The goal of this work was to investigate how far we can get from the character signal alone, without recourse to the more informative mechanisms, such as conditioning on word embeddings. The analysis of the results raised several questions regarding the design of the experiment: using the character input features alone how can one possibly predict phenomena like double-headed relative clauses or the morphological signaling of negation (Table 5) with such reliability? Is the system learning or just memorizing? A further possible confounding factor is the extreme sparsity of WALS features, which may not be modeled adequately by the weighted cross-entropy loss (Section 4) leading to possible classification randomness. We believe a significantly more focused and controlled set of experiments is required to address these concerns.

1 Introduction

The field of linguistic typology organizes the world’s languages according to their structural and functional features and helps to describe and explain the linguistic diversity (Song, 2013). In recent years there has been a growing interest in employing linguistic typology resources in natural language processing (Asgari and Schütze, 2017), where one of its primary applications has been work towards scaling up the existing language technologies to the long tail of world’s languages (O’Horan et al., 2016) for which the traditional resources are very scarce or missing altogether.

Typological resources such as PHOIBLE (Moran et al., 2014), Glottolog (Hammarström et al., 2018), PanPhon (Mortensen et al., 2016) and World Atlas of Language Structures (WALS) (Dryer and Haspelmath, 2013) have been successfully used in diverse speech and language tasks such as grapheme-to-phoneme conversion (Peters et al., 2017), multilingual language modeling (Tsvetkov et al., 2016), dependency parsing (Ammar et al., 2016) and text-to-speech (Tsvetkov, 2016).

In this work we investigate the task of learning linguistic typological information from multilingual text corpora. We frame this problem as a text classification task where, given a certain text of arbitrary length, one needs to determine the structural features of the corresponding language. The source for the features is the World Atlas of Language Structures (WALS) (Dryer and Haspelmath, 2013) that contains phonological, lexical, grammatical and other attributes gathered from descriptive materials for 2,679 languages.

Impressive progress has been achieved in the field of language identification (Lui, 2014) and accurate models are available for a large number of

languages (Jauhiainen et al., 2017). For the task at hand, however, in certain situations one cannot simply look up the required features by the language code having run the text through a language identifier. Such situations arise when insufficient amounts of training data are available for a language or no training data is available at all. As a hypothetical example, when applied to a text in Scots or Cornish, the language identification will assign the text to English and Welsh, respectively. This is not very helpful because, for this task, one is interested in the linguistic features that make Scots unique – possibly, as a stretch, its phonological relation to Old Norse (Heddle, 2010), or, in the case of Doric Scots, the Norwegian influence from the time of late Middle Ages (Lorvik, 2003).

This task is attractive because having an accurate linguistic typology detector can aid development work in speech and language fields. Correctly identifying broad phonetic features of an unknown language can help one build crude grapheme-to-phoneme rules and phoneme inventories for automatic speech recognition and text-to-speech. Simple morphological and syntactic analyzers can potentially be constructed given the knowledge of core syntactic and morphological attributes, such as subject-verb agreement, word order or gender categories. Given the hypothesis that basic word order and prosody are correlated (Bernard and Gervain, 2012), if the basic word order features can be reliably inferred, one can construct prosodic models of prominence. Finally, such models can potentially aid measuring the linguistic change. For example, given a text in 17th century Romani (Matras, 1995) (and assuming that it gets overall classified as modern Romani) one can possibly observe the features that it acquired or lost in the course of three hundred years.

The focus on this study is whether a reliable WALS feature neural network classifier can be constructed from multilingual, not necessarily parallel, text corpora. We describe the related typology prediction work in Section 2 and introduce our approach to predicting WALS features as a multi-label classification problem (Gibaja and Ventura, 2014). It’s worth noting that this task is different from the related work reported in the literature (Malaviya et al., 2017; Bjerva and Augenstein, 2018). First, the goal of the classifier is

to correctly infer the sparsely defined WALS features, rather than filling the missing gaps. Second, the classifier is trained on open text, rather than language embeddings produced as by-product of some other task (e.g., from parallel machine translation corpora). Finally, we make no assumptions about the input language of the text and employ no language identifying input features.

The goal of the experiments, described in Section 5, is to determine which features and groups thereof can be reliably inferred. In addition, we provide some of the results for various languages and their phylogenetic groupings. Since the task is reasonably novel, our goal is to provide a baseline, a very likely crude one, but one that can be gradually improved upon over time.

2 Related Work and Preliminaries

Related Work: A recent popular approach is to represent languages as dense real-valued vectors, referred to as *language embeddings*. It is assumed that these distributed language representations implicitly encode linguistic typology information. The language embeddings can be obtained by training a recurrent neural network language model (Mikolov et al., 2010) jointly for multiple languages (Tsvetkov et al., 2016; Östling and Tiedemann, 2017). Alternatively, the embeddings can be trained as part of other tasks, such as part-of-speech tagging (Bjerva and Augenstein, 2018) or neural machine translation (Malaviya et al., 2017).

Malaviya et al. (2017) note that existing typological databases, such as WALS, provide full feature specifications for only a handful of languages. In order to fill this gap they construct a massive many-to-one neural machine translation (NMT) system from 1017 languages into English (relying on a parallel database of biblical texts) and use the resulting language embeddings to successfully predict the missing information for the under-represented languages.

Bjerva and Augenstein (2018) produce language embeddings in the process of training a part-of-speech tagger for Uralic languages. At various stages of the training the authors constructed a logistic regression model that takes language embedding as an input and outputs a typological class the language belongs to according to WALS. They found that certain WALS features could be inferred from the embeddings with accuracy well

above the baseline.

Multi-Label Classification: Given an example text representation in an input feature space, $\mathbf{x} \in X$, the classification task consists of selecting a set of multiple applicable WALS feature labels $\{\lambda_i\}$ from a finite set of labels $L = \{\lambda_1, \lambda_2, \dots, \lambda_{N_L}\}$, where N_L is the number of WALS features (192 for the WALS version used in this work). Each candidate label takes its value from a set of disjoint classes $Y_i = \{y_j^i\}$, $1 \leq i \leq N_L$, corresponding to the values of a particular WALS feature λ_i . For example, language may or may not have a NUMBER OF GENDERS feature label present, but if it is present this feature cannot take the values of NONE and FOUR simultaneously. This scenario fits the *multi-label multi-class* classification problem (Gibaja and Ventura, 2014; Zhang and Zhou, 2014; Madjarov et al., 2012; Yang et al., 2009). Examples of natural language processing tasks where this type of problems arise is sentiment analysis (Liu and Chen, 2015) and text classification (Pestian et al., 2007).

Data Imbalance: As noted by Malaviya et al. (2017) and Littell et al. (2017), many typological databases are designed to suit the needs of theoretical linguistic typology, resulting in a sparse representation of features across languages (mostly due to intentional statistical balancing of features across language families and geographic areas). Also, for certain languages the maintainers are sometimes unable to obtain reliable description of linguistic attributes from the available linguistic sources, e.g. Comrie (2009). This situation is not perfect for statistical modeling because it results in heavy *data imbalance* between different types of features and complicates construction of machine learning models. A classifier constructed without regard to data imbalance will lean towards correctly predicting the majority class, which in case of WALS corresponds to missing or intentionally undefined features, while the “interesting” features with low coverage will receive corresponding proportion of classifier’s attention.

Approaches to data imbalance have been extensively studied in the literature (Japkowicz and Stephen, 2002; He and Garcia, 2009; Krawczyk, 2016) and the proposed remedies include altering the training data balance by *upsampling* (replicating cases from the minority), *downsampling* (removing cases from the majority), synthetically

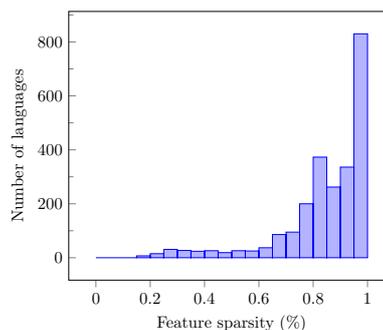


Figure 1: WALS features sparsity estimated as percentage of the features not attested for each language.

generating cases (He and Garcia, 2009; García et al., 2016) and design of special metrics (Charte et al., 2015). In this study we choose to keep the original training data as is in order not to disturb the original gentle balance between language representations and instead adjust the classifier optimization algorithm (King and Zeng, 2001) as well as introducing special logic for decoding the logits into posterior probability estimates.

3 Corpora

Text Corpus: For the training text data we used the second release of LTI LangID language identification corpus from CMU.¹ The core corpus contains training data for 847 languages, and some (possibly very tiny) amount of text for a total of 1146 languages. The data predominantly comes from Wikipedia text and many of the Bible translations (redistributable under Creative Commons licenses) as well as Europarl corpus of european parliamentary proceedings (Koehn, 2005). The core subset of the corpus contains languages for which sufficient text is available to generate quality models. Brown (2014) notes that there is no fixed minimum amount to be included in this category; generally, Bibles require less text than Wikipedia and languages with few lexically-similar languages require less than those with much lexical overlap. In this study we focus on the core subset of the corpus and treat various dialects of the same language (if these are present in the corpus) as distinct languages. The corpus is divided into training, development and test subsets, with the individual examples ranging from short words to single sentences and whole paragraphs.

¹<http://www.cs.cmu.edu/~ralf/langid.html>

Typology Dataset: We use World Atlas of Language Structures (WALS) (Dryer and Haspelmath, 2013) as a source of typological information for 2,679 languages. The 192 WALS typological multi-valued language features are organized into 152 chapters, each chapter corresponding to a particular phonological, morphological or syntactic linguistic property. For example, there are 18 chapters corresponding to WORD ORDER syntactic property where most chapters contains one typological feature, such as ORDER OF GENITIVE AND NOUN, while other chapters, such as ORDER OF NEGATIVE MORPHEME AND VERB contain 7 features, such as OBLIGATORY DOUBLE NEGATION (Dryer, 2013). The dataset is very sparse (Figure 1). For example, for 1,801 languages out of 2,679 only 20% (or less) of the WALS features are attested. Only 149 languages have 50% (or more) coverage.

Preparing the Data: First, we prune WALS by removing the languages for which no ISO 639-3 code is defined. This set includes 57 languages. In addition, we remove three languages for which no WALS features are attested. The training, development and test sets for neural network classifier are constructed by assigning to each example in LTI LangID dataset the corresponding WALS features. We match each LTI LangID example with the WALS features using the ISO 639-3 language code. Some LTI LangID language codes are in two-letter ISO 639-1 format which we convert to ISO 639-3 before attempting the lookup. Using this procedure we drop 338 languages for which no corresponding WALS entry can be reliably located using the ISO language code. The resulting dataset consists of 544 languages in the training set, 108 languages in the development set and 556 languages used for testing.

4 Methodology and Models

The goal of this study is to construct a model for inferring WALS features from text in many languages. The classifier design makes no special assumptions about code switching in the input text and does not use language identifying features rather than the text itself.

4.1 Embedding Layer

After combining the CMU LTI LangID and WALS datasets (described in Section 3) one is left with about 6,2M input sequences in 544 languages.

Tokenizing the training sequences into words and training parametrization of words as vectors, known as word embeddings (Mikolov et al., 2010), to be used as inputs to the neural network classifier is not going to work well because the amount of data at hand is not sufficient. In addition, some languages, such as Khmer and Burmese, require segmentation to obtain words, which in itself is a hard problem (Ding et al., 2016). Furthermore, the word embeddings don't provide us with a flexible way of capturing similar words in morphologically rich languages. To make this problem more tractable we employ character-level embeddings, which require fewer parameters than word-level embeddings and need no special preprocessing, such as complex tokenization (Zhang et al., 2015; Kim et al., 2016; Wieting et al., 2016; Irie et al., 2017). Similar to one of the competitive representations reported by Zhang and LeCun (2017) and unlike other approaches that operate on Unicode code points, e.g. (Jaech et al., 2016), we decompose the input text into UTF-8 byte sequences, which include white space characters. We consider two ways to model the UTF-8 byte-level embeddings.

Byte Unigrams: Let $\mathbf{x} = (x_1, x_2, \dots, x_T)$ be a byte representation of an input sequence. In the simplest scenario, similar to Xiao and Cho (2016), we treat each byte as a separate unigram from a small vocabulary V consisting of 256 values with the addition of an end-of-sentence and padding markers. At time t , byte input x_t is one-hot encoded into a vector \mathbf{c}_t and multiplied with the embedding matrix $W_c \in \mathbb{R}^{|V| \times d}$ to produce a d -dimensional embedding vector \mathbf{e}_t .

Byte n -grams: We also investigate the byte n -gram embeddings, where instead of individual bytes, the text is transformed into a sequence of UTF-8 byte n -grams. In other words, $\mathbf{x} = (\mathbf{x}_1^1, \mathbf{x}_1^2, \dots, \mathbf{x}_1^n, \dots, \mathbf{x}_{T-1}^{T-1}, \mathbf{x}_{T-1}^T, \mathbf{x}_T^T)$, where \mathbf{x}_i^j denotes a subsequence of bytes in \mathbf{x} from position i to position j inclusive, i.e. $\mathbf{x}_i^j = (x_i, x_{i+1}, \dots, x_j)$, where $\mathbf{x}_i^i = x_i$ and n is the maximum length of an n -gram window, decomposition similar to (Wieting et al., 2016). In this approach, the decomposition has the effect of lengthening the original byte sequence. We compute the d -dimensional embedding \mathbf{e}_t for an n -gram \mathbf{x}_t^{t+k} , $1 \leq k \leq n$, at time t as $\mathbf{e}_t = \frac{1}{k} \sum_{i=1}^k \mathbf{c}_i W_c$, where \mathbf{c}_i is a one-hot encoding of byte x_i and W_c is the

embedding matrix. Because n -grams are represented by individual byte aggregation, the dimensions of the embedding matrix can be compact, similar to the byte unigram representation.

Character n -grams as words: In this approach, the input text is transformed into sequences of Unicode character, rather than byte, n -grams. Each n -gram is treated as a unique undecomposable word from a possibly large vocabulary V and embeddings are constructed similarly to word embedding approaches (Mikolov et al., 2013).

4.2 Convolutional and Recurrent Layers

Given the embeddings, they can be treated as a kind of raw signal at character level to which one can apply one-dimensional temporal convolutions to extract important local context features. First introduced by Zhang et al. (2015), this approach has proven to be competitive to models built on word embeddings (Kim et al., 2016; Irie et al., 2017). We are adopting the same multiple convolutional layer configuration as the one reported by Xiao and Cho (2016). Applying the dropout (Srivastava et al., 2014) to the outputs of the embedding layer as well as the final convolution layer turned out to be effective.

Similar to others (Kim et al., 2016; Xiao and Cho, 2016; Jozefowicz et al., 2016; Vosoughi et al., 2016), we experiment with a hybrid architecture, where the outputs of a convolutional neural network (CNN) are used as inputs to a recurrent neural network (RNN). In our experiments, for an RNN we employ a bidirectional variant (Graves and Schmidhuber, 2005) of long short term memory (LSTM) model (Hochreiter and Schmidhuber, 1997), with an application of dropout.

4.3 Logits Layer and Optimization Strategies

We have looked into two approaches to optimization. In the first approach, we treat the problem as a standard multinomial logistic regression, where at each time step the network may output multiple non-exclusive labels. The forward and backward outputs corresponding to the last time step of a bidirectional LSTM are concatenated together and fed into the single fully-connected linear activation layer. Each output of this layer corresponds to a particular value of a WALs feature. There are 1316 outputs in total. We apply sigmoid non-linearities to the outputs of fully-connected layer and optimize all predictions \hat{y} against the

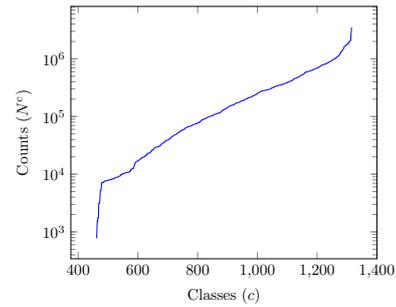


Figure 2: WALs feature value (class) counts displayed on a logarithmic scale. Classes are sorted by their counts. 461 classes out of 1316 are unobserved.

true labels y all at once using cross-entropy function (Bishop, 2006)

$$L(\theta) = -\frac{1}{N} \sum_{n=1}^N \sum_{i=1}^C y_n^i \log(\hat{y}_n^i(\mathbf{x}_n, \theta)) + r(\theta),$$

where θ represents network parameters, \mathbf{x} are the training sequences, C is the dimension of the prediction vector and r is an l_2 -norm regularization term. Recall that the task at hand is multi-label multi-class classification. Since WALs features are non-exclusive but their values corresponding to our predictions are not, we can only hope that the network learns that within each feature the values are independent.

To address this potential shortcoming we also tested an alternative strategy which constrains the universe of predicted values for each individual WALs feature to be mutually independent. In this scenario, we break the problem down into 192 tasks, one for each WALs feature, where each individual problem is treated as multinomial mutually-exclusive classification, somewhat similar to multi-task learning (Liu et al., 2016). For each task, a fully-connected layer is constructed that takes its input from the last time steps of the RNN and a softmax non-linearity is applied to each layer. The loss function in this case is the sum of individual softmax cross-entropy loss functions $L(\theta_i)$ for each task, $1 \leq i \leq 192$.

4.4 Dealing with Data Imbalance

In Section 3 we provided initial analysis of WALs feature sparsity based on feature value counts computed solely from WALs corpus (Figure 1). The dimension of difficulty involved in training a neural network WALs feature classifier on CMU LTI LangID data is demonstrated in Figure 2,

which shows the counts for all possible WALs feature values (corresponding to classes that the classifier has to predict) encountered in the training data. Significant proportion of classes (461 out of 1316) is not encountered in the training data for 544 languages. The distribution of counts for the majority of the remaining classes (approximately 700 in number) is approximately log-linear, while the remaining 155 classes are either very rare or very frequent.

To deal with this heavy class imbalance we employ the family of weighted cross-entropy loss functions defined as

$$L(\theta) = -\frac{1}{N} \sum_{n=1}^N \sum_{i=1}^C w(i) \mathbf{y}_n^i \log(\hat{\mathbf{y}}^i(\mathbf{x}_n, \theta)) + r(\theta),$$

where $w(c)$ is the weight function associated with class c which is defined as

$$w(c) = \begin{cases} N_{\mathcal{L}} / (N_c M_{\mathcal{L}}) & \text{if } N_c > 0, \\ 0 & \text{if } N_c = 0. \end{cases}$$

where $N_{\mathcal{L}}$ denotes the count of a WALs feature \mathcal{L} in the training data, N_c is the feature value count ($c \in \mathcal{L}$) and $M_{\mathcal{L}} = |\mathcal{L}|$ is the number of values for feature \mathcal{L} . This reciprocal frequency definition of a weight function $w(c)$ above is inspired by King and Zeng (2001). The purpose of the function is to penalize the frequent classes and boost the rare ones. The unattested classes do not contribute to the overall loss.²

Since 461 classes are not observed in the training data, additional modification to the training regime consists of masking out the logits corresponding to these classes before applying sigmoid or softmax (in the case of multi-task optimization) non-linearities.

5 Experiments

5.1 Dataset Preprocessing

The dataset details are shown in Table 1 where for training, development and test sets the number of languages and the corresponding total number of sequences are shown. Statistics was computed on UTF-8 bytes (\mathcal{B}) and Unicode characters (\mathcal{C}). One of the important indicators is the length of individual sequences - some of the sequences corre-

²For the multi-task approach we also tried to introduce label weights defined as $N/(192N_{\mathcal{L}})$ that scale the individual task loss functions, but this modification did not lead to improvement in the models.

spond to short words while others represent sentences or even the entire paragraphs. The presence of very long sequences is indicated by the length (in bytes) of the longest sequence in each dataset (denoted $S_{\max}^{\mathcal{B}}$). Instead of performing sentence splitting on individual sequences (which may be tricky for languages with limited means of denoting sentence breaks) we retain all the sequences which are between five and 600 characters long, omitting the rest from the training and testing. The resulting total number of byte or character tokens and the mean and standard deviation of sequence lengths are then computed for bytes ($N^{\mathcal{B}}, \mu^{\mathcal{B}}, \sigma^{\mathcal{B}}$) and characters ($N^{\mathcal{C}}, \mu^{\mathcal{C}}, \sigma^{\mathcal{C}}$). Pruning out the very long sequences makes the training process more tractable by reducing the training time, while retaining reasonably high variance in sequence lengths, as indicated by the values of standard deviation.

5.2 Network Architecture Details

The experiments involve three network configurations, each corresponding to a particular type of the embedding layer introduced in Section 4.

Embedding Layer: The dimension d of the embedding vector is 8 for the individual byte embeddings, 32 for byte n -gram embeddings and 256 for character n -gram embeddings. The dropout with probability 0.5 is applied to the embedding layer (Srivastava et al., 2014). The maximum length of byte n -gram is 7, while for character n -grams we generate n -grams up to the length of 5. The character n -grams are hashed in order convert the strings into integer quantities. The number of hash buckets is set to 2^{14} . When training the embedding we initialize it using normal distribution $(\mu_e, \sigma_e) = (0, \frac{1}{\sqrt{d}})$.

Convolutional Layer: The parameters for the convolutional are somewhat similar to one of configurations in (Xiao and Cho, 2016): There are three one-dimensional convolution layers containing 20, 40 and 60 filters, respectively. Receptive field sizes r for each layer are 5, 5 and 3. The stride parameter is set to 1. Rectified linear units (ReLU) are used in each layer (Glorot et al., 2011). Batch normalization is applied before each layer (Ioffe and Szegedy, 2015). Each convolution layer is followed by a max-pooling layer with filter size r' set to 2. Dropout with probability 0.5 is applied to the last max-pooling layer.

Type	N_L	N	Bytes (\mathcal{B})				Characters (\mathcal{C})		
			$S_{\max}^{\mathcal{B}}$	$N^{\mathcal{B}}$	$\mu^{\mathcal{B}}$	$\sigma^{\mathcal{B}}$	$N^{\mathcal{C}}$	$\mu^{\mathcal{C}}$	$\sigma^{\mathcal{C}}$
train	544	6,199,201	20.5K	1,057M	176.0	130.0	887M	147.5	108.5
dev	108	79,856	9.9K	15.9M	199.4	152.7	12M	150.2	115.2
test	556	226,235	7.2K	39.2M	174.7	131.4	32.8M	146.0	109.7

Table 1: Dataset details showing, for each dataset type, the number of languages (N_L), the total number of predictions (N) and some statistics computed on bytes (\mathcal{B}) and characters (\mathcal{C}), respectively.

Chapter Type	N	A (%)	P	R	F_1
COMPLEX SENTENCES	244K	58.5	0.67	0.45	0.54
LEXICON	439K	63.4	0.82	0.27	0.41
MORPHOLOGY	458K	50.2	0.65	0.35	0.45
NOMINAL CATEGORIES	1.4M	50.1	0.59	0.40	0.44
NOMINAL SYNTAX	403K	56.3	0.75	0.25	0.38
OTHER	9.6K	26.5	0.81	0.19	0.31
PHONOLOGY	1.2M	61.9	0.70	0.40	0.50
SIGN LANGUAGES	55K	56.6	0.90	0.11	0.20
SIMPLE CLAUSES	1.2M	59.1	0.59	0.40	0.47
VERBAL CATEGORIES	1.2M	56.8	0.83	0.24	0.38
WORD ORDER	2.7M	60.1	0.79	0.22	0.34

Table 2: Metrics for WALS features grouped by WALS chapter type.

Macroarea	N_L	N	A (%)	P	R	F_1
Eurasia	133	4M	58.95	0.86	0.35	0.47
Africa	45	796K	51.16	0.80	0.45	0.55
North America	104	870K	51.35	0.81	0.42	0.52
South America	112	150K	51.51	0.83	0.38	0.49
Papunesia	145	215K	53.22	0.84	0.37	0.49

Table 3: Metrics for WALS features grouped by language macro-area.

Bidirectional LSTM: The RNN consists of stacked two-layer bidirectional LSTM containing 128 cells each. Dropout is applied to each layer with probability of 0.5. Uniform weight initialization scheme from (Glorot and Bengio, 2010) was used. Residual connections are added to the second LSTM layer (Wang and Tian, 2016).

Optimization: The models are trained using AdaDelta (Zeiler, 2012) with $\rho = 0.95$ and $\epsilon = 10^{-8}$. We use exponential learning rate decay, with initial learning rate set to $5 * 10^{-5}$, reasonably slow decay factor of 0.9 and number of decay steps set to $3 * 10^5$. L_2 regularization is applied to the recurrent layer weights, with the weight scaling factor set to 0.05. In addition, value of 10 is used to clip the global gradients. The training batch size is set to 8.

5.3 Results and Analysis

When computing the various metrics we ignore the undefined WALS feature values focusing on

attested features only, relying on the fact that during training the weighted loss function alleviates the inherent imbalance between the WALS classes. After pruning out the WALS features and the individual values unattested in the training data, we are predicting 1316 possible values (classes) of 183 WALS features (labels).³

Selecting the Best Model: We used an accuracy metric computed on all the WALS features encountered in the test set in order to select the best out of the architectures described earlier. Our baseline was byte unigram LSTM-RNN configurations with no convolutional layers for which an accuracy of 52.3% was achieved. We tested the configurations described in the previous section against the baseline and found that the best performing architecture is a byte 7-gram CNN-LSTM that achieves the accuracy of 57.2% in the regular (non multi-task) training mode. The character 5-gram configuration achieved a slightly worse accuracy of 57.1% and was also found to be more memory inefficient due to the size of the embedding (which is necessary in order to treat character n -grams as word-like units). A surprising discovery was that the multi-task-like training did not perform as well as we had hoped with all the configurations scoring below 50%. In addition, the multi-task training was significantly slower (taking one day longer to converge) due to running numerically more complex optimization.

Chapter Types: Results for all the WALS features aggregated over chapter types are shown in Table 2, where, for each chapter type, the total number of predictions (N), accuracy (A), precision (P), recall (R) and F_1 scores are displayed. Despite reasonable precision values, the recall is substantially lower for all the chapter types which is due to the high number of predicted false negatives. The three chapter types with most accu-

³Due to space limitation, some of the tables below contain partial results. The full tables are submitted as supplementary material.

Family	<i>R</i>	<i>N</i>	<i>A</i> (%)	<i>P</i>	<i>R</i>	<i>F</i> ₁
Tol	1	26.4K	70.0	0.82	0.84	0.82
Harákmbet	2	3.5K	69.5	0.79	0.81	0.80
Cofán	3	6.5K	68.8	0.80	0.82	0.81
Uru-Chipaya	4	10.8K	67.6	0.81	0.82	0.81
Kiowa-Tanoan	5	368	66.7	0.67	0.67	0.67
Dagan	6	33.2K	65.2	0.80	0.82	0.81
Uralic	7	240K	65.0	0.83	0.70	0.74
Dravidian	8	176K	64.6	0.82	0.73	0.76
Oksapmin	9	7.3K	64.0	0.79	0.80	0.79
Korean	10	162K	63.2	0.79	0.82	0.80
Zaparoan	11	7.7K	62.5	0.77	0.80	0.78
Basque	12	80K	61.9	0.79	0.81	0.80
Tai-Kadai	13	59K	60.8	0.79	0.79	0.79
Indo-European	14	2M	60.4	0.83	0.50	0.59
...

Family	<i>R</i>	<i>N</i>	<i>A</i> (%)	<i>P</i>	<i>R</i>	<i>F</i> ₁
...
Macro-Ge	67	65K	49.0	0.74	0.67	0.69
Yele	68	12.8K	48.9	0.72	0.74	0.73
Niger-Congo	69	345K	48.1	0.78	0.53	0.61
Tucanoan	70	153K	47.8	0.74	0.66	0.68
Arauan	71	62K	47.3	0.72	0.74	0.73
Na-Dene	72	44K	47.1	0.73	0.70	0.70
Urarina	73	9.6K	46.4	0.71	0.72	0.71
Bosavi	74	5.9K	45.8	0.71	0.71	0.71
Guaicuruan	75	7K	41.4	0.67	0.69	0.68
Central Sudanic	76	10K	37.2	0.66	0.67	0.67
West Bougainville	77	3.6K	35.7	0.64	0.64	0.64
Eskimo-Aleut	78	2.2K	28.5	0.50	0.57	0.52
Left May	79	861	25.0	0.50	0.50	0.50
Chiquito	80	6.2K	22.2	0.56	0.60	0.58

Table 4: WALS individual feature metrics grouped by 80 language families and ranked (*R*) by accuracy (*A*). 14 best (left) and worst (right) scoring language families are shown.

Id	<i>R</i>	Name	<i>N</i>	<i>A</i> (%)	<i>P</i>	<i>R</i>	<i>F</i> ₁
90G	1	DOUBLE HEADED RELATIVE CLAUSES	307	100.00	1.00	1.00	1.00
143G	2	MORPHOLOGICAL SIGNALING OF NEG.	128K	99.53	1.00	0.50	0.67
144X	3	VERB INIT. WITH CLAUSE-FINAL NEG.	19.5K	98.26	0.99	0.50	0.67
130A	4	FINGER AND HAND	87K	96.92	0.98	0.50	0.66
90C	5	POSTNOMINAL RELATIVE CLAUSES	66.8K	95.90	0.99	0.34	0.50
144P	6	NEGSVO ORDER	47.6K	95.59	0.99	0.33	0.50
144H	7	NEGSVO ORDER	38.6K	94.49	0.98	0.33	0.50
18A	8	ABSENCE OF COMMON CONSONANTS	68K	94.47	0.99	0.25	0.40
25B	9	ZERO MARKING OF A AND P ARG.	30K	93.98	0.97	0.50	0.66
144Q	11	SNESVO ORDER	46K	92.44	0.98	0.25	0.40
58B	12	NUMBER OF POSSESSIVE NOUNS	33K	91.79	0.98	0.25	0.40
80A	13	VERBAL NUMBER AND SUPPLETION	37K	91.62	0.98	0.25	0.40
137A	14	N-M PRONOUNS	31K	90.79	0.97	0.33	0.50
58A	15	OBLIGATORY POSSESSIVE INFL.	33K	90.37	0.95	0.50	0.66
11A	16	FRONT ROUNDED VOWELS	68K	89.79	0.97	0.25	0.40
135A	18	RED AND YELLOW	25K	88.21	0.97	0.25	0.40
73A	19	THE OPTATIVE	46K	87.54	0.94	0.50	0.65
6A	20	UVULAR CONSONANTS	68K	86.61	0.97	0.25	0.40
7A	24	GLOTTALIZED CONSONANTS	68K	84.15	0.98	0.14	0.25
...
36A	157	THE ASSOCIATIVE PLURAL	43K	34.56	0.84	0.25	0.39
1A	158	CONSONANT INVENTORIES	67K	33.58	0.87	0.20	0.33
45A	159	POLITENESS IN PRONOUNS	41K	33.54	0.83	0.25	0.38
53A	160	ORDINAL NUMERALS	67K	32.24	0.90	0.14	0.25
144G	161	DOUBLE NEG. IN SVO LANG.	2.8K	31.71	0.76	0.19	0.31
22A	162	INFL. SYNTHESIS OF THE VERB	25K	31.39	0.89	0.17	0.28
143B	163	OBLIGATORY DOUBLE NEG.	7.6K	29.57	0.91	0.13	0.22
54A	164	DISTRIBUTIVE NUMERALS	44K	28.81	0.90	0.14	0.25
50A	168	ASYMMETRICAL CASE MARKING	41K	26.12	0.55	0.20	0.29
123A	170	RELATIVIZATION ON OBLIQUES	25K	24.45	0.85	0.20	0.32
62A	171	ACTION NOMINAL CONSTRUCTIONS	32K	22.97	0.80	0.12	0.22
133A	173	BASIC COLOUR CATEGORIES	25K	18.92	0.77	0.13	0.22
144M	175	MULT. NEG. CONSTRUCTIONS IN SOV	6K	17.36	0.91	0.11	0.20
144F	179	OBLIGATORY DOUBLE NEG. IN SVO	3.2K	10.79	0.87	0.15	0.25
143C	180	OPTIONAL DOUBLE NEG.	6.4K	10.57	0.82	0.12	0.20
144E	181	MULT. NEG. CONSTRUCTIONS IN SVO	5.2K	8.23	0.82	0.10	0.18
144D	182	OPTIONAL DOUBLE NEG. IN SOV	3.6K	8.15	0.85	0.17	0.28
90D	183	INTERNALLY HEADED RELATIVE CLAUSES	5.7K	4.85	0.68	0.33	0.45

Table 5: Metrics for individual WALS features ranked (*R*) by accuracy (*A*) in descending order.

rate (according to *A*) predictions are LEXICON, PHONOLOGY and WORD ORDER. These contain lexical, phonological and word order-related features. Interestingly, the least accurate chapter type is MORPHOLOGY, even though we intuitively expect the results for the morphological features to be on par with the lexical features.

Language Macro-Areas: Another informative comparison is to group the predictions over WALS linguistic macro-areas (Hammarström and Donohue, 2014) shown in Table 3, where N_L is the number of languages tested for the particular macro-area, N is the total number of predictions,

and metrics, similar to the ones employed when aggregating over chapter types, are shown. The best results according to accuracy (*A*) and precision (*P*) correspond to the languages of Eurasia. We hypothesize that this can potentially be explained by two factors: First, the proportion of the training data for Eurasian languages is significantly higher than for the other languages and, second, the Eurasian languages are likely to be better documented, resulting in more detailed WALS descriptions and hence lower feature sparsity.

Language Families: Table 4 shows the results aggregated over 28 language families out of 80, where the 14 languages on the left correspond to the best performing group and the 14 languages on the right to the worst performing group (according to accuracy *A*). Language rank is *R* and *N* denotes the total number of predictions. With the exception of a couple of outliers, most of the top performing languages have relatively high and balanced values of precision and recall. Interestingly enough, the top most accurate language families correspond to very small languages of South and Central America. In the case of Tol, Harákmbet and Uru-Chipaya, the families consist of a single language spoken by around a thousand (or less) speakers. Predictions for these very low-resource languages are significantly more accurate than for some much larger and better documented families in the list, such as Uralic, Dravidian, Tai-Kadai and Indo-European, although the precision and recall values are overall roughly in the same range. Among the poorly scoring (in terms of accuracy) language families shown in the table on the right, the poor scores for Niger-Congo and Central Sudanic language families can be singled out. The

result for Niger-Congo family is especially disappointing because this is one of the major language families both in terms of number of distinct languages and the number of speakers. Despite low accuracy, however, the precision value of 0.78 for Niger-Congo family is reasonable.

Individual Features: Table 5 shows various metrics for the short (best) head and long (worst) tail of 183 individual WALS features, ranked by accuracy (A). For each feature, the corresponding WALS feature identifier (Id), its rank (R), name and the number of predictions (N) is shown along with the corresponding metrics. For most of the features, precision completely dominates the recall due to high number of false negatives. The accurately predicted features (with accuracy over 80%) and poorly predicted ones come from diverse WALS chapter types with no clear “winning” type to declare. For example, both NEGSOV ORDER and NEGVO ORDER (from WORD ORDER chapter) are reliably and very well predicted, while the prediction of OPTIONAL DOUBLE NEGATION IN SOV feature from the same chapter type is extremely poor. The same observation holds for other chapter types, such as NOMINAL SYNTAX. It is interesting to note that some features from the PHONOLOGY type, such as FRONT ROUNDED VOWELS, are among the most accurate.

6 Conclusion

In this study we approached the problem of predicting the attested sparse WALS features as a multi-label classification problem. We have shown that by building a reasonably standard recurrent neural network classifier following the recipes from the existing literature, combined with a simple reciprocal frequency weighting for alleviating the class imbalance, we can reliably predict at least some of individual WALS features. An interesting finding that confirms the finding of Malaviya et al. (2017) is that the features come from a variety of linguistic types. Despite these promising initial findings, much work still remains: We need more sophisticated techniques, such as SMOTE (Jeatrakul et al., 2010), to make classifier more robust against the WALS feature sparsity. Furthermore, to mirror some of the conclusions of Wieting et al. (2016), in our situation a simpler architecture, perhaps not even a neural one, may have performed better than state-of-the-

art CNN-LSTM hybrid model.⁴ In addition to improving our models, we would also like to investigate the correlations between different groups of WALS features, provide a more in-depth typological analysis for performance of various features and test our models against the languages not seen in the training data.

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⁴We will be releasing the code used in the experiments into public domain.

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