# The LMU System for the CoNLL-SIGMORPHON 2017 Shared Task on Universal Morphological Reinflection

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## Abstract

We present the LMU system for the CoNLL-SIGMORPHON 2017 shared task on universal morphological reinflection, which consists of several subtasks, all concerned with producing an inflected form of a paradigm in different settings. Our solution is based on a neural sequence-to-sequence model, extended by preprocessing and data augmentation methods. Additionally, we develop a new algorithm for selecting the most suitable source form in the case of multi-source input, outperforming the baseline by $5.7\%$ on average over all languages and settings. Finally, we propose a fine-tuning approach for the multi-source setting, and combine this with the source form detection, increasing accuracy by a further $4.6\%$ on average.

## 1 Introduction

Many of the world's languages have a rich morphology, i.e., make use of surface variations of lemmata in order to express certain properties, like the tense or mood of a verb. This makes a variety of natural language processing tasks more challenging, as it increases the number of words in a language drastically; a problem morphological analysis and generation help to mitigate. However, a big issue when developing methods for morphological processing is that for many morphologically rich languages, there are only few or no relevant training data available, making it impossible to train state-of-the-art machine learning models (e.g., (Faruqui et al., 2016; Kann and Schütze, 2016b; Aharoni et al., 2016; Zhou and Neubig, 2017)). This is the motivation for the CoNLL-SIGMORPHON-2017 shared task on universal morphological reinflection (Cotterell et al., 2017a), which animates the development of systems for as many as 52 different languages in 6 different low-resource settings for morphological reinflection: to generate an inflected form, given a target morphological tag and either the lemma (task 1) or a partial paradigm (task 2). An example is

(use, V;3;SG;PRS) $\mapsto$ uses

In this paper, we describe the LMU system for the shared task. Since it depends on the language and the amount of resources available for training which method performs best, our approach consists of a modular system. For most medium- and high-resource, as well as some low-resource settings, we make use of the state-of-the-art encoder-decoder (Cho et al., 2014a; Sutskever et al., 2014; Bahdanau et al., 2015) network MED (Kann and Schütze, 2016b), while extending the training data in several ways. Whenever the given data are not sufficient, we make use of the baseline system, which can be trained on fewer instances.

While we submit solutions for every language and setting, our main focus is on task 2 of the shared task and the main contributions of this paper correspondingly address a multi-source input setting: (i) We develop CIS ("choice of important sources"), a novel algorithm for selecting the most appropriate source form for a target tag from a partially given paradigm, which is based on edit trees (Chrupała, 2008). (ii) We propose to cast the task of multi-source morphological reinflection as a domain adaptation problem. By fine-tuning on forms from a partial paradigm, we improve the performance of a neural sequence-to-sequence model for most shared task languages.

Our final methods, averaged over languages, outperform the official baseline by $7.0\%$, $18.5\%$, and $16.5\%$ for task 1 and $8.7\%$, $10.1\%$, and



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10.3% for task 2 for the low-, medium-, and high-resource settings, respectively.

Furthermore, our submitted sytem—a combination of our methods with the baseline system—surpasses the baseline's accuracy on test for both tasks as well as all languages and settings. Differences in performance are between 8.69% (task 1 low) and 17.94% (task 1 medium).

## 2 Morphological Reinflection

The paradigm of a lemma $w_l$ is a set of tuples of inflected forms $f_k$ and tags $t_k$ describing the properties of the inflected word, which we formally denote as:

$$\pi(w_l) = \left\{ \left( f_k[w_l], t_k \right) \right\}_{t_k \in T(w_l)} \quad (1)$$

with $T(w_l)$ being the set of possible tags for $w_l$.

An example is the following paradigm of the Spanish lemma *soñar*:

$$\pi(\text{soñar}) = \left\{ \left( \textit{sueño}, \text{1SgPresInd} \right), \ldots, \left( \textit{soñaran}, \text{3PlPastSbj} \right) \right\}$$

The shared task has two subtasks: **task 1** consists of predicting a certain form $f_i[w_l]$, given the lemma $w_l$ and the target tag $t_i$. For **task 2**, one or more source forms are given for each lemma (multi-source input). Thus, additional information about the way a lemma is inflected is known and can be leveraged.

## 3 Preprocessing Methods

We apply the following preprocessing methods.

**String preprocessing.** We determine for each language if it is predominantly prefixing or suffixing, using the same algorithm as the shared task baseline system (Cotterell et al., 2017a). For prefixing languages, we invert all words. An example for the prefixing language Navajo is:

chidí → ídihc

**New character handling.** The source and target vocabularies for the languages are constructed using the respective training and development sets. Therefore, out-of-vocabulary symbols can appear in the test sets, resulting in symbols the model has no information about. In order to address this, we substitute such characters by a special `NEW` symbol and train the model on it by including it in the additional training samples we create, cf. §4. In the output, `NEW` is substituted back by the new characters in the input in order of appearance. An example from the German development data is:

Phloëm → Phlo`NEW`m

**Tag extension.** Explicit information is usually handled better by machine learning methods than implicit information. Therefore, we search for optional subtag slots, in contrast to those that are always occupied by some value, e.g., an optional *negation* subtag, in contrast to the part-of-speech subtag which, for most languages, is always either *Verb*, *Noun* or *Adjective*, but never empty. For all optional subtags, we artificially introduce a negated form.

## 4 Training Data Augmentation Methods

**Additional source-target form pairs.** We collect all forms belonging to the same lemma. We then add additional samples by constructing source-target combinations for other sources than the lemma, using the members of each paradigm. For the two samples $lemma_i \rightarrow word_1$ and $lemma_i \rightarrow word_2$ we can introduce the new samples $word_1 \rightarrow word_2$ and $word_2 \rightarrow word_1$.[1]

**Autoencoding samples.** We further create samples for a sequence autoencoding task, i.e., we add mappings of words to themselves, with a special copy tag **`A`**. No morphological tags are given. This is a way to multi-task train on autoencoding the input string and reinflection, as we maximize the joint log-likelihood

$$\mathcal{L}(\boldsymbol{\theta}) = \sum_{(w_l, t_s, t_t) \in \mathcal{T}} \log p_{\boldsymbol{\theta}} \left( f_t(w_l) \mid e(f_s(w_l), t_t) \right) + \sum_{w \in \mathcal{W}} \log p_{\boldsymbol{\theta}}(w \mid e(w)) \quad (2)$$

for the training data $\mathcal{T}$, source and target tags $t_s$ and $t_t$, a lemma $w_l$ and an encoding function $e$ depending on $\boldsymbol{\theta}$, as well as a set of strings $\mathcal{W}$. We apply two variants: autoencoding the lemmata and forms from the original training set, or using *random* strings for this. Random strings are produced in the following way. We first construct all possible bigrams $\mathcal{B}$ from the vocabulary of the language. We then combine those with a random sequence of characters $r$ of a random length between

[1] The respective source and target tags are part of the input, but omitted here for clarity.

1 and 4 in the following way: $b_1 + b_2 + r + b_3 + b_4$ for $b_i \in \mathcal{B}$. Constructing random strings like this has the positive side-effect that we can add a `NEW` to the vocabulary.

**Rule-based data generation.** We imitate a rule-based system by, given a source form and a target form, defining the prefix (resp. suffix) of a word as the word minus the longest common suffix (resp. prefix). We then create an additional training example by generating a random string $s$ and prepending (resp. appending) source and target prefixes (resp. suffixes) to $s$. For example, in German, we can find the following rule for the 2nd person singular form:

$$\text{*en} \rightarrow \text{*st}$$

From this we can create additional training instances like the following.

$$\text{(jfgdgfen, V;2;SG;PRS)} \mapsto \text{jfgdgfst}$$
$$\text{(Ahggen, V;2;SG;PRS)} \mapsto \text{Ahggst}$$

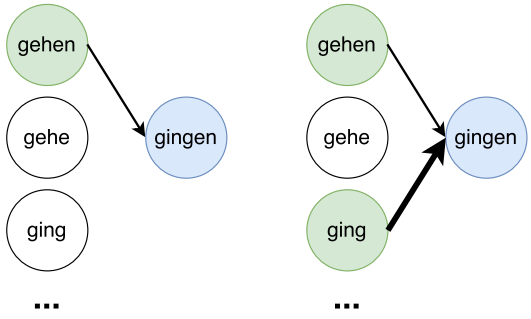
We apply this procedure to all pairs of a source and a target tag that appear less than $t$ times in train for a certain threshold $t$.

## 5 System Architecture

We apply the encoder-decoder network MED (Kann and Schütze, 2016a), due to its success in last year's edition of the shared task (Cotterell et al., 2016). While we extend it by new training data augmentation methods and, for task 2, the additional algorithms described below, we do not make changes to the model's architecture. We will shortly describe MED and the shared task baseline system in this section.

### 5.1 MED

**Encoder.** The format of the input of the encoder is the same as in (Kann and Schütze, 2016a), but with a small modification to be able to handle unlabeled data: Given the set of morphological subtags M that each target tag is composed of (e.g., the tag *1SgPresInd* contains the subtags *1*, *Sg*, *Pres* and *Ind*), and the alphabet $\Sigma$ of the language of application, our input is of the form $(\mathbf{A} \mid \text{M}^*)\ \Sigma^*$, i.e., it consists of *either* a sequence of subtags *or* the symbol **A** signaling that the input is not annotated and should be autoencoded, and (in both cases) the character sequence of the input word. All parts of the input are represented by embeddings.




(a) The lemma is the only accepted source form.

(b) Additional source forms with a higher priority than the lemma have been determined.

Figure 1: Comparison of the traditional view (left) and the result of CIS (right). Possible source forms in green, the target form in blue. Thickness of the arrows represents priorities of source forms. Most forms of the paradigm have been omitted because of space limitations.

We encode the input $x = x_1, x_2, \ldots, x_{T_x}$ using a bidirectional gated recurrent neural network (GRU) (Cho et al., 2014b). We then concatenate the forward and backward hidden states to obtain the input $h_i$ for the decoder.

**Decoder.** The decoder is a uni-directional attention-based GRU, defining a probability distribution over strings in $\Sigma^*$:

$$p(y \mid x) = \prod_{t=1}^{T_y} p(y_t \mid y_1, \ldots, y_{t-1}, s_t, c_t),$$

with $s_t$ being the decoder hidden state for time $t$ and $c_t$ being a context vector, calculated using the encoder hidden states together with attention weights. A detailed description of the encoder-decoder model can be found in (Bahdanau et al., 2015).

### 5.2 Baseline System

The shared task baseline system (**BL**) is well-suited for low-resource settings. It first aligns each input and output string, and than extracts possible prefix or suffix substitution rules from the training data. At test time, it applies the most suitable one in the following way: Every input is searched for the longest contained prefix or suffix and the rule belonging to the affix and given target tag is applied to obtain the output. Whether prefixes or suffixes are used depends on the language and is determined using the training set.

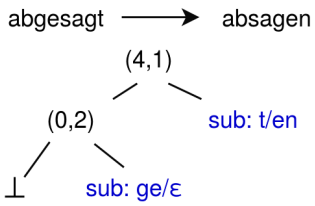



Figure 2: Edit tree for the transformation from *abgesagt* "canceled" to *absagen* "to cancel". Each node contains the length of the parts before and after the respective LCS, e.g., the leftmost node contains the length of the parts before and after the LCS of *abge* and *ab*. The prefix *sub* indicates that the node is a substitution operation.

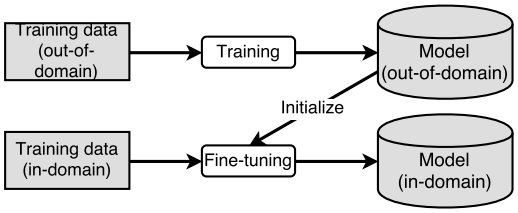



Figure 3: Overview of a fine-tuning setup. In our case, "in-domain" refers to the partial paradigm to be completed; "out-of-domain" refers to all other paradigms.

## 6 Choice of Important Sources

As our **choice of important sources (CIS) algorithm** is based strongly on edit trees (Chrupała, 2008), we will introduce them first.

**Edit trees.** An edit tree $e(\sigma, \tau)$ is a way to specify a transformation between a source string $\sigma$ and a target string $\tau$ (Chrupała, 2008). It is constructed by first determining the longest common substring (LCS) (Gusfield, 1997) of $\sigma$ and $\tau$ and then modeling the prefix and suffix pairs of the LCS recursively. In the case of an empty LCS, $e(\sigma, \tau)$ corresponds to the substitution operation that replaces $\sigma$ with $\tau$. Figure 2 shows an example.

**CIS.** The entire task of paradigm completion is built upon the notion that the members of a paradigm are not independent. However, for many languages, some slots of a paradigm are more dependent on each other: For example, *gehen*, *gehe* and *ging* are all forms of the same German paradigm, but when aiming to produce the 3rd person plural past tense form *gingen*, the task is easier when starting from the (more similar) form *ging*. In fact, in many cases, the entire paradigm is *completely deterministic* when the right paradigm slots are known. A set of forms that determines all other inflected forms is called *principal parts*.

(Cotterell et al., 2017b) use this property of morphologically rich languages to induce topologies in order to jointly decode entire paradigms and to thus make use of all known forms. However, they suppose to be able to compute and use good estimates for the probabilities $p(f_i(w_l)|f_j(w_l))$ for source form $f_j(w_l)$ and target form $f_i(w_l)$, since they use at least 632 entire paradigms per part of speech and language for training. Using a minimum spanning tree, they approximate a solution to the maximum-a-posteriori (MAP) inference problem.

In order to be able to apply our approach to low-resource settings, we focus instead on finding the *best source form* for each target form in a language, and CIS works as follows. We calculate edit trees for each pair $(f_j(w_l), f_i(w_l))$ for each lemma $w_l$ in the training data. We then count the number of different edit trees for each pair of source and target tag $(t_j, t_i)$ and build an *importance list* for each tag $t_i$, giving higher priorities to source tags with lower counts. The intuition behind this is that the fewer different edit trees appear in the training set, the more deterministic the paradigm slot $i$ is, given a certain source slot $j$.

At test time, we find the form from the given slots of the paradigm which has the highest importance score, and use it to generate the target form. Note that, as the lemma is always given, there will never be a need to use a worse source form than the lemma.

## 7 Fine-Tuning for Multi-Source Input

For sequence-to-sequence models for neural machine translation, it has been shown that specialized models for a certain domain are able to obtain better performances than general ones (Luong and Manning, 2015). One way to perform such a *domain adaptation* is fine-tuning: a general model, which has been trained on out-of-domain data, is further trained on (newly) available in-domain data, cf. Figure 3. This brings the conditional probability $p(y_1, ..., y_m|x_1, ..., x_n)$ for an output sequence $(y_1, ..., y_m)$ given an input sequence $(x_1, ..., x_n)$ closer to the target distribution.

Here, we propose to improve multi-source morphological reinflection by treating each paradigm as a separate domain and performing "domain adaptation" everytime a new paradigm should be completed by the model.

In particular, we have one base model (for

| $n \leq 1.5$ | $1.5 < n < 10$ | $10 \leq n$ |
|---|---|---|
| danish | arabic | albanian |
| english | bengali | armenian |
| norwegian-bokmal | bulgarian | basque |
| norwegian-nynorsk | czech | catalan |
| | dutch | haida |
| | estonian | hindi |
| | faroese | italian |
| | finnish | khaling |
| | french | persian |
| | georgian | portuguese |
| | german | quechua |
| | hebrew | sorani |
| | hungarian | spanish |
| | icelandic | turkish |
| | irish | urdu |
| | kurmanji | welsh |
| | latin | |
| | latvian | |
| | lithuanian | |
| | lower-sorbian | |
| | macedonian | |
| | navajo | |
| | northern-sami | |
| | polish | |
| | romanian | |
| | russian | |
| | scottish-gaelic | |
| | serbo-croatian | |
| | slovak | |
| | slovene | |
| | swedish | |
| | ukrainian | |

Table 1: Average amount n of sources given per paradigm, for the development set.

each setting and language), trained on all available training examples. The original training data corresponds to *out-of-domain data* in a domain adaptation setting. At test time, we construct for each partial paradigm $\mathcal{P}_{known}$ all possible training examples in the way described in the paragraphs about additional source-target form pairs and autoencoding in §4. Thus, for $|\mathcal{P}_{known}| = n$, we end up with (up to) $n * (n-1) + N_a$ in-domain samples for fine-tuning where $N_a$ is the number of autoencoding training samples. We then for each partial paradigm fine-tune the original base model on all examples constructed from $\mathcal{P}_{known}$, which match the *in-domain data* for domain adaptation. Thus, we end up with a different fine-tuned model for each partial paradigm in the test set.

Our method is expected to perform best in a setting in which many forms of each paradigm are given as input, e.g., when $n$ is big. Table 1 indicates for which language we would therefore expect could performance.

# 8 Experiments

## 8.1 Systems

**Task1.** For task 1, we apply **MED***: MED in combination with all preprocessing methods mentioned in §3 and the following data augmentations. We create additional source-target form pairs where possible and create autoencoding samples, random ones as well as from the original data. Further, we create 5 additional rule-based samples for each existing sample of all source-target tag combinations that appear less than $t = 10$ times in the training set for a language.

We employ ensembles of 5 MED* models, which are trained for 90 (low and medium) or 45 (high) epochs. Ensembling is done by majority voting.

**Task2.** We again apply MED*. However, for task 2 we do not create rule-based samples.[2] Models for the low-resource, medium-resource and high-resource settings are trained for 45, 30 and 20 epochs, respectively. For task 2, we do not use ensembling.

At test time, we preprocess each newly incoming paradigm in the same way as the training data, except for the creation of random copy samples. We then *fine-tune* the base model for each new paradigm according to §7 for 25 additional epochs. Additionally, we choose the best source form for each required target tag and predict each inflected form for this input (**MED*+FT+CIS**).

The limited amount of data makes it impossible to obtain competitive performance using MED* for some languages and settings (especially for languages with only few given slots per paradigm), even after applying all data augmentation methods described above. Thus, we apply the baseline model for those cases, but combine it with CIS (cf. §6) to improve its performance (**BL+CIS**). We do not apply preprocessing or data augmentation methods for BL, as they would not influence its performance.

**Shared task submission.** The best approach depends on both the language and the setting. Thus, our final submission for each case is obtained by either BL, BL+CIS, the MED* ensemble, or MED*+FT+CIS, selected using the accuracy on the development set.

[2]Using rule-based examples for training leads to worse performance of the fine-tuned system, even though the base system turns out to be better. Thus, we do not use it.

| | low | | | medium | | | high | | |
|---|---|---|---|---|---|---|---|---|---|
| | BL | MED* | MED* (ENS) | BL | MED* | MED* (ENS) | BL | MED* | MED* (ENS) |
| albanian | **0.216** | 0.102 | 0.129 | 0.661 | 0.849 | **0.878** | 0.781 | 0.966 | **0.975** |
| arabic | 0.215 | 0.237 | **0.298** | 0.400 | 0.804 | **0.842** | 0.477 | 0.930 | **0.952** |
| armenian | 0.378 | 0.444 | **0.488** | 0.766 | 0.897 | **0.914** | 0.891 | 0.972 | **0.975** |
| bulgarian | 0.331 | 0.437 | **0.480** | 0.750 | 0.814 | **0.837** | 0.900 | 0.969 | **0.974** |
| catalan | 0.552 | 0.560 | **0.598** | 0.832 | 0.903 | **0.930** | 0.942 | 0.981 | **0.983** |
| czech | **0.408** | 0.318 | 0.341 | 0.807 | 0.815 | **0.856** | 0.904 | 0.927 | **0.937** |
| danish | 0.598 | 0.636 | **0.654** | 0.781 | 0.830 | **0.845** | 0.891 | 0.934 | **0.960** |
| dutch | **0.537** | 0.500 | 0.521 | 0.717 | 0.828 | **0.862** | 0.868 | 0.968 | **0.971** |
| english | 0.762 | 0.831 | **0.852** | 0.902 | 0.928 | **0.940** | 0.950 | 0.964 | **0.968** |
| faroese | 0.307 | 0.347 | **0.386** | 0.587 | 0.595 | **0.672** | 0.747 | 0.817 | **0.867** |
| finnish | **0.162** | 0.120 | 0.147 | 0.425 | 0.682 | **0.754** | 0.785 | 0.939 | **0.954** |
| french | 0.630 | 0.579 | **0.635** | 0.761 | 0.789 | **0.820** | 0.836 | 0.889 | **0.914** |
| georgian | 0.712 | 0.802 | **0.845** | 0.900 | 0.925 | **0.928** | 0.940 | 0.991 | **0.995** |
| german | 0.537 | 0.541 | **0.593** | 0.715 | 0.772 | **0.800** | 0.812 | 0.894 | **0.912** |
| hebrew | 0.279 | 0.335 | **0.366** | 0.400 | 0.798 | **0.831** | 0.558 | 0.987 | **0.991** |
| hindi | 0.310 | 0.781 | **0.782** | 0.866 | 0.964 | **0.974** | 0.940 | **1.000** | **1.000** |
| hungarian | 0.172 | 0.300 | **0.346** | 0.417 | 0.708 | **0.763** | 0.711 | 0.856 | **0.874** |
| icelandic | 0.342 | 0.341 | **0.364** | 0.614 | 0.647 | **0.689** | 0.761 | 0.873 | **0.913** |
| italian | 0.449 | 0.392 | **0.467** | 0.738 | 0.920 | **0.927** | 0.799 | **0.978** | 0.974 |
| latvian | **0.621** | 0.483 | 0.536 | 0.851 | 0.834 | **0.861** | 0.910 | 0.965 | **0.977** |
| lower-sorbian | 0.343 | 0.451 | **0.488** | 0.705 | 0.788 | **0.817** | 0.860 | 0.966 | **0.973** |
| macedonian | 0.500 | 0.577 | **0.664** | 0.823 | 0.901 | **0.913** | 0.919 | 0.957 | **0.964** |
| navajo | 0.184 | 0.166 | **0.198** | 0.313 | 0.415 | **0.460** | 0.383 | 0.838 | **0.897** |
| northern-sami | 0.154 | 0.136 | **0.174** | 0.357 | 0.639 | **0.711** | 0.611 | 0.954 | **0.968** |
| norwegian-nynorsk | 0.508 | 0.489 | **0.559** | 0.633 | 0.671 | **0.687** | 0.783 | 0.883 | **0.923** |
| persian | 0.273 | 0.405 | **0.457** | 0.654 | 0.892 | **0.913** | 0.776 | 0.999 | **1.000** |
| polish | 0.419 | 0.366 | **0.431** | 0.752 | 0.751 | **0.780** | 0.894 | 0.909 | **0.925** |
| portuguese | 0.603 | 0.633 | **0.684** | 0.929 | 0.938 | **0.944** | 0.974 | 0.986 | **0.993** |
| quechua | 0.172 | 0.567 | **0.615** | 0.681 | 0.965 | **0.977** | 0.947 | **1.000** | **1.000** |
| russian | **0.428** | 0.319 | 0.366 | 0.750 | 0.763 | **0.801** | 0.820 | 0.909 | **0.919** |
| scottish-gaelic | 0.480 | 0.600 | **0.620** | 0.520 | 0.940 | **0.960** | – | – | – |
| serbo-croatian | 0.213 | 0.286 | **0.324** | 0.658 | 0.812 | **0.844** | 0.840 | 0.900 | **0.920** |
| slovak | 0.419 | 0.467 | **0.495** | 0.707 | 0.788 | **0.795** | 0.852 | 0.940 | **0.960** |
| slovene | 0.474 | 0.494 | **0.522** | 0.819 | 0.865 | **0.883** | 0.898 | 0.966 | **0.981** |
| spanish | **0.586** | 0.465 | 0.554 | 0.854 | 0.891 | **0.910** | 0.906 | 0.965 | **0.974** |
| swedish | 0.543 | 0.590 | **0.607** | 0.737 | 0.772 | **0.796** | 0.854 | 0.901 | **0.914** |
| turkish | 0.143 | **0.280** | 0.255 | 0.331 | 0.801 | **0.852** | 0.729 | 0.977 | **0.982** |
| ukrainian | **0.729** | 0.350 | 0.393 | 0.715 | 0.757 | **0.775** | 0.863 | 0.929 | **0.934** |
| urdu | 0.303 | 0.669 | **0.687** | 0.861 | 0.955 | **0.962** | 0.958 | **0.996** | 0.995 |
| welsh | 0.150 | 0.340 | **0.460** | 0.540 | 0.910 | **0.920** | 0.670 | **0.990** | **0.990** |
| basque | 0.000 | 0.140 | **0.180** | 0.020 | 0.860 | **0.870** | 0.060 | **0.990** | **0.990** |
| bengali | 0.440 | 0.610 | **0.680** | 0.750 | **0.980** | **0.980** | 0.840 | **0.990** | **0.990** |
| estonian | 0.226 | 0.242 | **0.271** | 0.624 | 0.796 | **0.832** | 0.762 | 0.985 | **0.992** |
| haida | 0.340 | 0.480 | **0.570** | 0.560 | **0.920** | 0.910 | 0.690 | **0.970** | **0.970** |
| irish | **0.318** | 0.188 | 0.222 | 0.447 | 0.626 | **0.694** | 0.543 | 0.891 | **0.929** |
| khaling | 0.039 | 0.157 | **0.184** | 0.184 | 0.879 | **0.901** | 0.538 | 0.995 | **0.998** |
| kurmanji | **0.823** | 0.818 | 0.620 | 0.884 | 0.904 | **0.916** | 0.922 | 0.934 | **0.943** |
| latin | **0.160** | 0.139 | 0.028 | 0.368 | 0.430 | **0.489** | 0.456 | 0.735 | **0.795** |
| lithuanian | **0.235** | 0.168 | 0.193 | 0.530 | 0.592 | **0.618** | 0.647 | 0.867 | **0.906** |
| norwegian-bokmal | 0.690 | 0.722 | **0.743** | 0.798 | 0.820 | **0.838** | 0.906 | 0.907 | **0.925** |
| romanian | **0.441** | 0.335 | 0.392 | 0.702 | 0.715 | **0.764** | 0.804 | 0.863 | **0.893** |
| sorani | 0.205 | 0.175 | **0.232** | 0.528 | 0.794 | **0.823** | 0.643 | 0.899 | **0.910** |
| Average: | 0.386 | 0.421 | **0.456** | 0.647 | 0.804 | **0.832** | 0.751 | 0.902 | **0.916** |

Table 2: Accuracies for task 1, for BL, MED* and MED* ensembles. Upper part: development languages; lower part: surprise languages.

### 8.2 MED Hyperparameters

We use the same hyperparameters for all MED models, i.e., all languages, tasks and amounts of resources. In particular, we keep them fixed to the following. Encoder and decoder RNNs each have 100 hidden units and the embeddings size is 300. For training we use ADADELTA (Zeiler, 2012) with minibatch size 20. Following Le et al. (2015), we initialize all weights in the encoder, decoder and the embeddings except for the GRU weights in the decoder to the identity matrix. Biases are initialized to zero. We use dropout with a coefficient of 0.5. As this is the model we use to produce test results for the shared task, we report

| | Task 1 | Task 2 |
|---|---|---|
| Low | 100 | 535 |
| Medium | 994 | 2285 |
| High | 9825 | 8578 |

Table 3: Average amount of training examples per task and resource quantity.

the best numbers obtained on the development set during training ("early stopping"). We compare the 1-best accuracy of all systems, i.e., the percentage of predictions that match the true answer exactly.

### 8.3 Data

The official shared task data consists of sets for 52 different languages, 2 tasks and 3 different settings with varying amount of resources.[3] An overview of the (averaged) amount of samples per task and setting is given in Table 3. Development and test sets are the same for all settings for each respective task and language. The gold labels for the test set are not published yet, so the experiments in this paper are performed on the development set.

### 8.4 Results

We compare our approaches to the official shared task baseline. Detailed results for task 1 and task 2 are shown in Table 2 and Table 4, respectively.

**Task 1.** Table 2 shows the results obtained by MED*, both for single models and ensembles. As can be seen, MED* already outperforms the baseline for the majority of languages in all settings; in average by $0.035$, $0.157$ and $0.151$, respectively. MED*'s performance is worse for the low data quantity than for the others. This is an expected result, as neural networks are known to require a huge amount of training instances.

Ensembling increases the final accuracy for all settings, by an average of $0.035$ (low), $0.028$ (medium) and $0.014$ (high).

**Task 2.** As can be seen in Table 4, combining BL and CIS outperforms BL on its own for many languages, especially in the low-resource setting. The highest improvements for the low-, medium- and high-resource setting are for Hungarian ($0.362$), Latin ($0.440$) and Latin ($0.429$), respectively. For some languages, e.g., Catalan, Danish or Urdu, choosing a good source form seems to not be important. For a few languages, results even get worse. We will discuss some of those cases in §9. Overall, however, we obtain $0.087$ (low), $0.066$ (medium) and $0.019$ (high) improvement on average over all languages, which clearly shows the usefulness of CIS.

MED* on its own does not achieve competitive performance for task 2. We attribute this to the limited number of different lemmata given for training, resulting in an overfitting model, learning, e.g., to produce certain character combinations for certain tags. However, MED*+FT+CIS outperforms both BL as well as BL+CIS for many languages in the medium- and high-resource settings and even in some low-resource scenarios. Comparing the obtained accuracies with Table 1, it gets obvious that languages with a higher amount of given source forms per paradigm achieve better results after fine-tuning, many times reaching a higher accuracy than BL, even in the low-resource setting. In contrast, fine-tuning works poorly for languages with $\leq 1.5$ given source forms per paradigm. In total, using MED*+FT+CIS, we obtain an average improvement of $0.068$ (low), $0.101$ (medium) and $0.103$ (high) over the baseline.

### 8.5 Official Shared Task Evaluation

Our submitted system obtained average accuracies of $0.4659$ (low), $0.8264$ (medium) and $0.947$ (high) for task 1, and $0.6776$ (low), $0.8202$ (medium) and $0.8852$ (high) for task 2, respectively. This corresponds to place 5 of 18, 3 of 19 and 7 of 15 for the high-, medium- and low-resource settings of task 1, respectively. Remarkably, the difference to the best system for the two higher settings is less than $0.01$.

Among 3 submissions for task 2, our system comes first. It beats the baseline by $17.16$ (low), $15.54$ (medium) and $10.84$ (high).

## 9 Remaining Challenges

Certain parts of our system do not perform as well for some languages as we would expect. In this section we will discuss those cases in more detail.

**CIS.** For some languages, e.g., Danish or English, CIS does not influence the performance. This might be due to those languages not having paradigm slots that are regularly closer to certain slots than others.

One other problem for the algorithm are training instances that consist of multiple separate words, e.g., the edit trees for "ride a bike" $\mapsto$

[3] A list of all languages can be found in Tables 2 and 4.

| | low | | | | medium | | | | high | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | BL | BL+ CIS | MED* | MED*+ FT+CIS | BL | BL+ CIS | MED* | MED*+ FT+CIS | BL | BL+ CIS | MED* | MED*+ FT+CIS |
| albanian | 0.160 | 0.249 | 0.000 | **0.619** | **0.882** | 0.280 | 0.016 | 0.865 | 0.942 | 0.434 | 0.240 | **0.960** |
| arabic | 0.380 | 0.428 | 0.011 | **0.706** | 0.553 | 0.704 | 0.059 | **0.907** | 0.566 | 0.733 | 0.533 | **0.953** |
| armenian | 0.722 | 0.855 | 0.001 | **0.933** | 0.785 | 0.962 | 0.210 | **0.969** | 0.856 | 0.806 | 0.517 | **0.983** |
| bulgarian | 0.553 | **0.592** | 0.006 | 0.571 | 0.640 | 0.646 | 0.200 | **0.747** | 0.819 | 0.810 | 0.677 | **0.911** |
| catalan | **0.942** | 0.938 | 0.000 | 0.877 | 0.958 | **0.970** | 0.266 | 0.962 | 0.965 | 0.976 | 0.759 | **0.992** |
| czech | 0.307 | **0.346** | 0.008 | 0.312 | 0.610 | **0.635** | 0.160 | 0.580 | **0.841** | 0.839 | 0.429 | 0.806 |
| danish | **0.567** | **0.567** | 0.284 | 0.287 | **0.753** | **0.753** | 0.541 | 0.410 | **0.827** | **0.827** | 0.673 | 0.680 |
| dutch | 0.588 | **0.666** | 0.057 | 0.608 | 0.796 | **0.932** | 0.509 | 0.796 | 0.845 | 0.965 | 0.812 | **0.969** |
| english | **0.784** | **0.784** | 0.544 | 0.576 | 0.832 | 0.832 | **0.852** | 0.784 | 0.900 | 0.900 | 0.900 | **0.924** |
| faroese | 0.513 | **0.592** | 0.000 | 0.171 | 0.559 | **0.674** | 0.234 | 0.578 | 0.651 | 0.738 | 0.430 | **0.761** |
| finnish | 0.517 | **0.629** | 0.017 | 0.581 | 0.720 | 0.743 | 0.143 | **0.899** | 0.709 | 0.772 | 0.470 | **0.948** |
| french | 0.864 | 0.876 | 0.000 | **0.877** | 0.893 | 0.936 | 0.379 | **0.951** | 0.982 | 0.959 | 0.824 | **0.983** |
| georgian | 0.793 | **0.853** | 0.000 | 0.834 | 0.900 | **0.922** | 0.532 | 0.909 | 0.933 | 0.954 | 0.793 | **0.966** |
| german | 0.610 | **0.647** | 0.123 | 0.625 | 0.662 | 0.748 | 0.255 | **0.764** | 0.705 | 0.813 | 0.619 | **0.874** |
| hebrew | 0.380 | 0.683 | 0.012 | **0.786** | 0.417 | 0.701 | 0.217 | **0.895** | 0.547 | 0.743 | 0.596 | **0.950** |
| hindi | 0.698 | 0.719 | 0.000 | **0.970** | 0.746 | 0.867 | 0.040 | **0.970** | 0.961 | 0.563 | 0.719 | **1.000** |
| hungarian | 0.255 | 0.617 | 0.000 | **0.627** | 0.453 | 0.823 | 0.238 | **0.824** | 0.585 | 0.877 | 0.503 | **0.949** |
| icelandic | 0.439 | **0.546** | 0.000 | 0.333 | 0.531 | **0.683** | 0.083 | 0.588 | 0.617 | **0.753** | 0.380 | 0.751 |
| italian | 0.769 | **0.843** | 0.000 | 0.809 | 0.839 | 0.901 | 0.075 | **0.927** | 0.901 | 0.896 | 0.503 | **0.976** |
| latvian | 0.790 | **0.839** | 0.001 | 0.565 | 0.852 | **0.926** | 0.330 | 0.825 | 0.877 | **0.953** | 0.705 | 0.951 |
| lower-sorbian | 0.362 | **0.532** | 0.003 | 0.509 | 0.670 | **0.811** | 0.302 | 0.769 | 0.866 | **0.878** | 0.650 | 0.867 |
| macedonian | 0.396 | **0.562** | 0.001 | 0.367 | 0.832 | **0.858** | 0.175 | 0.740 | 0.942 | **0.964** | 0.749 | 0.876 |
| navajo | 0.306 | **0.404** | 0.008 | 0.313 | 0.385 | 0.502 | 0.088 | **0.517** | 0.408 | 0.593 | 0.282 | **0.650** |
| northern-sami | 0.314 | **0.485** | 0.000 | 0.243 | 0.499 | **0.841** | 0.028 | 0.758 | 0.562 | 0.905 | 0.201 | **0.912** |
| Norwegian-nynorsk | 0.439 | **0.445** | 0.127 | 0.122 | **0.604** | **0.604** | 0.452 | 0.341 | **0.610** | 0.579 | 0.560 | 0.555 |
| persian | 0.822 | 0.159 | 0.000 | **0.990** | 0.911 | 0.185 | 0.203 | **0.997** | 0.889 | 0.190 | 0.854 | **1.000** |
| polish | 0.506 | **0.596** | 0.002 | 0.327 | 0.694 | **0.787** | 0.170 | 0.704 | 0.794 | **0.831** | 0.619 | 0.820 |
| portuguese | 0.951 | **0.973** | 0.001 | 0.934 | 0.969 | **0.987** | 0.243 | 0.969 | 0.975 | **0.995** | 0.741 | 0.991 |
| quechua | 0.973 | **1.000** | 0.000 | 0.972 | 0.973 | 0.973 | 0.234 | **0.996** | 0.972 | **0.999** | 0.796 | **0.999** |
| russian | 0.412 | **0.503** | 0.039 | 0.382 | 0.830 | **0.843** | 0.400 | 0.816 | 0.900 | 0.907 | 0.756 | **0.915** |
| scottish-gaelic | 0.449 | **0.498** | 0.004 | 0.441 | 0.441 | **0.506** | 0.087 | 0.490 | – | – | – | – |
| serbo-croatian | 0.285 | 0.291 | 0.001 | **0.363** | 0.570 | 0.601 | 0.095 | **0.683** | 0.863 | 0.850 | 0.166 | **0.898** |
| slovak | 0.647 | **0.705** | 0.006 | 0.447 | 0.720 | **0.779** | 0.295 | 0.659 | 0.777 | **0.805** | 0.530 | 0.789 |
| slovene | 0.616 | **0.834** | 0.000 | 0.583 | 0.767 | **0.886** | 0.352 | 0.834 | 0.798 | **0.943** | 0.636 | 0.933 |
| spanish | 0.787 | 0.882 | 0.000 | **0.901** | 0.911 | 0.895 | 0.192 | **0.971** | 0.954 | 0.908 | 0.717 | **0.978** |
| swedish | 0.421 | **0.475** | 0.049 | 0.208 | 0.635 | **0.795** | 0.282 | 0.643 | 0.723 | **0.843** | 0.583 | 0.789 |
| turkish | 0.124 | 0.624 | 0.000 | **0.805** | 0.613 | 0.876 | 0.303 | **0.977** | 0.825 | 0.921 | 0.697 | **0.994** |
| ukrainian | 0.523 | **0.594** | 0.007 | 0.411 | **0.734** | 0.709 | 0.285 | 0.655 | **0.808** | 0.760 | 0.452 | 0.773 |
| urdu | 0.670 | 0.670 | 0.010 | **0.883** | 0.680 | 0.680 | 0.027 | **0.953** | **0.991** | 0.488 | 0.221 | 0.982 |
| welsh | 0.601 | 0.349 | 0.000 | **0.857** | 0.693 | 0.864 | 0.127 | **0.939** | 0.752 | 0.903 | 0.258 | **0.960** |
| basque | 0.040 | 0.180 | 0.005 | **0.890** | 0.051 | 0.182 | 0.021 | **0.891** | – | – | – | – |
| bengali | 0.661 | **0.928** | 0.036 | 0.780 | 0.847 | **0.963** | 0.100 | 0.906 | 0.847 | **0.965** | 0.238 | 0.933 |
| estonian | 0.385 | 0.734 | 0.001 | **0.806** | 0.551 | 0.767 | 0.064 | **0.953** | 0.581 | 0.779 | 0.273 | **0.951** |
| haida | 0.554 | 0.810 | 0.000 | **0.937** | 0.802 | 0.849 | 0.002 | **0.937** | – | – | – | – |
| irish | 0.317 | **0.439** | 0.045 | 0.375 | 0.424 | 0.493 | 0.137 | **0.592** | 0.474 | 0.530 | 0.411 | **0.692** |
| khaling | 0.247 | 0.495 | 0.011 | **0.973** | 0.546 | 0.627 | 0.279 | **0.992** | 0.840 | 0.659 | 0.638 | **0.996** |
| kurmanji | 0.633 | **0.648** | 0.003 | 0.449 | 0.790 | **0.798** | 0.279 | 0.695 | 0.875 | 0.844 | 0.679 | **0.878** |
| latin | 0.336 | **0.594** | 0.000 | 0.157 | 0.449 | **0.889** | 0.112 | 0.691 | 0.493 | **0.922** | 0.301 | 0.820 |
| lithuanian | 0.536 | **0.669** | 0.006 | 0.487 | 0.615 | **0.831** | 0.059 | 0.744 | 0.662 | **0.879** | 0.302 | 0.876 |
| norwegian-bokmal | 0.417 | **0.438** | 0.396 | 0.306 | **0.590** | **0.590** | 0.576 | 0.340 | **0.750** | **0.750** | 0.715 | 0.667 |
| romanian | 0.151 | **0.232** | 0.008 | 0.062 | 0.630 | **0.715** | 0.077 | 0.561 | 0.773 | **0.786** | 0.284 | 0.744 |
| sorani | 0.534 | 0.532 | 0.000 | **0.630** | 0.661 | 0.561 | 0.065 | **0.879** | 0.646 | 0.599 | 0.488 | **0.898** |
| Average: | 0.520 | **0.607** | 0.035 | 0.588 | 0.682 | 0.748 | 0.220 | **0.783** | 0.783 | 0.802 | 0.549 | **0.886** |

Table 4: Accuracies for task 2. All systems are described in the text. Upper part: development languages; lower part: surprise languages.

"riding a bike" and "hike" $\mapsto$ "hiking" are not the same, even though they should be. Such cases potentially confuse the algorithm. A solution could be to detect training examples which consist of more than one token and split them up, in order to just consider the inflecting word.

**Fine-tuning.** For some settings and languages, e.g., Danish or Bokmål, the fine-tuned model obtains a lower accuracy than the base MED* model. While this might seem strange at first, when comparing to Table 1, it gets clear that this is mainly the case for languages where, besides the lemma,

no forms of a paradigm are given. This results in the model being fine-tuned on autoencoding the lemma, and thus a strong bias to copy the input, which can hurt performance. A possible solution might be to apply a combination of fine-tuning and multi-domain training as proposed, e.g., by Chu et al. (2017) for neural machine translation. We leave respective experiments for future work.

## 10 Conclusion

We presented the LMU system for the CoNLL-SIGMORPHON 2017 shared task on universal morphological reinflection, which is based on an encoder-decoder network. We introduced two new methods for handling multi-source morphological reinflection: CIS, a source form selection algorithm based on edit trees and a fine-tuning approach similar in spirit to domain adaptation. On average over all participating languages, our approaches outperform the official shared task baseline for both tasks and all settings.

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## References

Roee Aharoni, Yoav Goldberg, and Yonatan Belinkov. 2016. Improving sequence to sequence learning for morphological inflection generation: The biu-mit systems for the sigmorphon 2016 shared task for morphological reinflection. In *SIGMORPHON*.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In *ICLR*.

Kyunghyun Cho, Bart Van Merriënboer, Dzmitry Bahdanau, and Yoshua Bengio. 2014a. On the properties of neural machine translation: Encoder-decoder approaches. *arXiv preprint 1409.1259* .

Kyunghyun Cho, Bart Van Merriënboer, Çalar Gülçehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014b. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In *EMNLP*.

Grzegorz Chrupała. 2008. *Towards a machine-learning architecture for lexical functional grammar parsing*. Ph.D. thesis, Dublin City University.

Chenhui Chu, Raj Dabre, and Sadao Kurohashi. 2017. An empirical comparison of simple domain adaptation methods for neural machine translation. *arXiv preprint 1701.03214* .

Ryan Cotterell, Christo Kirov, John Sylak-Glassman, Géraldine Walther, Ekaterina Vylomova, Patrick Xia, Manaal Faruqui, Sandra Kübler, David Yarowsky, Jason Eisner, and Mans Hulden. 2017a. The CoNLL-SIGMORPHON 2017 shared task: Universal morphological reinflection in 52 languages. In *CoNLL-SIGMORPHON*.

Ryan Cotterell, Christo Kirov, John Sylak-Glassman, David Yarowsky, Jason Eisner, and Mans Hulden. 2016. The SIGMORPHON 2016 shared task—morphological reinflection. In *SIGMORPHON*.

Ryan Cotterell, John Sylak-Glassman, and Christo Kirov. 2017b. Neural graphical models over strings for principal parts morphological paradigm completion. In *EACL*.

Manaal Faruqui, Yulia Tsvetkov, Graham Neubig, and Chris Dyer. 2016. Morphological inflection generation using character sequence to sequence learning. In *NAACL-HLT*.

Dan Gusfield. 1997. *Algorithms on strings, trees and sequences: computer science and computational biology*. Cambridge university press.

Katharina Kann and Hinrich Schütze. 2016a. MED: The LMU system for the SIGMORPHON 2016 shared task on morphological reinflection. In *SIGMORPHON*.

Katharina Kann and Hinrich Schütze. 2016b. Single-model encoder-decoder with explicit morphological representation for reinflection. In *ACL*.

Quoc V Le, Navdeep Jaitly, and Geoffrey E Hinton. 2015. A simple way to initialize recurrent networks of rectified linear units. *CoRR* abs/1504.00941.

Minh-Thang Luong and Christopher D Manning. 2015. Stanford neural machine translation systems for spoken language domains. In *IWSLT*.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In *NIPS*.

Matthew D Zeiler. 2012. ADADELTA: An adaptive learning rate method. *CoRR* abs/1212.5701.

Chunting Zhou and Graham Neubig. 2017. Multi-space variational encoder-decoders for semi-supervised labeled sequence transduction. *arXiv preprint 1704.01691* .