(Un)solving Morphological Inflection: Lemma Overlap Artificially Inflates Models’ Performance

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Abstract
In the domain of Morphology, Inflection is a fundamental and important task that gained a lot of traction in recent years, mostly via SIGMORPHON’s shared-tasks. With average accuracy above 0.9 over the scores of all languages, the task is considered mostly solved using relatively generic neural seq2seq models, even with little data provided. In this work, we propose to re-evaluate morphological inflection models by employing harder train-test splits that will challenge the generalization capacity of the models. In particular, as opposed to the naïve split-by-form, we propose a split-by-lemma method to challenge the performance on existing benchmarks. Our experiments with the three top-ranked systems on the SIGMORPHON's 2020 shared-task show that the lemma-split presents an average drop of 30 percentage points in macro-average for the 90 languages included. The effect is most significant for low-resourced languages with a drop as high as 95 points, but even high-resourced languages lose about 10 points on average. Our results clearly show that generalizing inflection to unseen lemmas is far from being solved, presenting a simple yet effective means to promote more sophisticated models.

1 Introduction
In recent years, morphological (re)inflection tasks in NLP have gained a lot of attention, most notably with the introduction of SIGMORPHON’s shared tasks (Cotterell et al., 2016, 2017, 2018; Vylomova et al., 2020) in tandem with the expansion of UniMorph (McCarthy et al., 2020), a multi-lingual dataset of inflection tables. The shared-tasks sample data from UniMorph includes lists of triplets in the form of (lemma, features, form) for many languages, and the shared-task organizers maintain standard splits for a fair system comparison.

The best-performing systems to-date in all inflection shared-tasks are neural sequence-to-sequence models used in many NLP tasks. An LSTM-based model won 2016’s task (Kann and Schütze, 2016), and a transformer came on top in 2020 (Canby et al., 2020). In 2020’s task the best model achieved exact-match accuracy that transcended 0.9 macro-averaged over up to 90 languages from various language families and types. This trend of high results recurred in works done on data collected independently as well (e.g. Malouf, 2017, Silfverberg and Hulden, 2018, inter alia).

Interestingly, the averaged results of 2020’s shared-task include languages for which very little data was provided, sometimes as little as a couple of hundreds of examples. This has led to a view considering morphological inflection a relatively simple task that is essentially already solved, as reflected in the saturation of the results over the year and the declining submissions to the shared tasks.\(^1\) This also led the community to gravitate towards works attempting to solve the same (re)inflection tasks with little or no supervision (McCarthy et al., 2019; Jin et al., 2020; Goldman and Tsarfaty, 2021).

However, before moving on we should ask ourselves whether morphological inflection is indeed solved or may the good performance be attributed to some artifacts in the data. This was shown to be true for many NLP tasks in which slight modifications of the data can result in a more challenging dataset, e.g., the addition of unanswerable questions to question answering benchmarks (Rajpurkar et al., 2018), or the addition of expert-annotated minimal pairs to a variety of tasks (Gardner et al., 2020). A common modification is re-splitting the data such that the test set is more challenging and closer to the intended use of the models in the wild (Søgaard et al., 2021). As the performance on morphological inflection models seems to have saturated on high scores, a similar rethinking of the data used is warranted.

\(^1\)The shared task of 2021 had seen only two submissions (Pimentel et al., 2021).
In this work we propose to construct more difficult datasets for morphological (re)inflection by splitting them such that the test set will include no forms of lemmas appearing in the train set. This splitting method will allow assessing the models in a challenging scenario closer to their desired function in practice, where training data usually includes full inflection tables and learning to inflect the uncovered lemmas is the target.

We show, by re-splitting the data from task 0 of SIGMORPHON’s 2020 shared-task, that the proposed split reveals a greater difficulty of morphological inflection. Retesting 3 of the 4 top-ranked systems of the shared-task on the new splits leads to a decrease of 30 points averaged over the systems for all 90 languages included in the shared-task. We further show that the effect is more prominent for low-resourced languages, where the drop can be as large as 95 points, though high-resourced languages may suffer from up to a 10 points drop as well. We conclude that in order to properly assess the performance of (re)inflection models and to drive the field forward, the data and related splits should be carefully examined and improved to provide a more challenging evaluation, more reflective of their real-world use.

2 (Re)inflection and Memorization

Inflection and reinflection are two of the most dominant tasks in computational morphology. In the inflection task, the input is a lemma and a feature-bundle, and we aim to predict the respective inflected word-form. In reinflection, the input is an inflected word-form along with its features bundle, plus a feature-bundle without a form, and we aim to predict the respective inflected-form for the same lemma. The training input in SIGMORPHON’s shared-tasks is a random split of the available (lemma,form,features) triplets such that no triplet occurring in the train-set occurs in the test-set.²

In such a setting, models can short-cut their way to better predictions in cases where forms from the same lemma appear in both the train and test data. This may allow models to memorize lemma-specific alternations that make morphological inflection a challenging task to begin with. Consider for example the notoriously unpredictable German plurality marking, where several allomorphs are associated with nouns with no clear rule governing the process. Kind, for example, is pluralized with the suffix -er resulting in Kinder tagged as NOM;PL. Assuming a model saw this example in the train set it is pretty easy to predict Kindern for the same lemma with DAT;PL features,³ but without knowledge of the suffix used to pluralize Kind the predictions Kinden and Kinds are just as likely.

3 Related Work

Many subfields of NLP and machine learning in general suggested hard splits as means to improve the probing of models’ ability to solve the underlying task, and to make sure models do not simply employ loopholes in the data.

In the realm of sentence simplification, Narayan et al. (2017) suggested the WEBSPLIT dataset, where models are required to split and rephrase complex sentences associated with a meaning representation over a knowledge-base. Aharoni and Goldberg (2018) found that some facts appeared in both train and test sets and provided a harder split denying models the ability to use memorized facts. Aharoni and Goldberg (2020) also suggested a general splitting method for machine translation such that the domains are as disjoint as possible.

In semantic parsing, Finegan-Dollak et al. (2018) suggested a better split for parsing natural language questions to SQL queries by making sure that queries of the same template do not occur in both train and test, while Lachmy et al. (2021) split their HEXAGONS data such that any one visual pattern used for the task cannot appear in both train and test. Furthermore, Loula et al. (2018) adversarially split semantic parsing for navigation data to assess their models’ capability to use compositionality. In spoken language understanding Arora et al. (2021) designed a splitting method that will account for variation in both speaker identity and linguistic content.

In general, concerns regarding data splits and their undesirable influence on model assessments led Gorman and Bedrick (2019) to advocate random splitting instead of standard ones. In reaction, Søgaard et al. (2021) pointed to the flaws of random splits and suggested adversarial splits to challenge models further. Here we call for paying attention to the splits employed in evaluating morphological models, and improve on them.

²This is true for all SIGMORPHON’s inflection shared tasks, save the paradigm completion task of 2017.

³The addition of the dative marker -n is very regular.
Table 1: Exact-match accuracy and edit-distance for our baseline and 3 of the 4 top-ranked systems of SIGMORPHON’s 2020 shared-task, all reported on the original split of the shared-task (form split) and on our harder lemma split. Best system per column is in **bold**.

| Split           | Accuracy Form | Accuracy Lemma | Edit Distance Form | Edit Distance Lemma |
|-----------------|---------------|----------------|--------------------|---------------------|
| DeepSpin-02     | 0.90          | 0.76           | 0.23               | 0.58                |
| CULing          | 0.88          | 0.63           | 0.29               | 1.02                |
| Base trm-single | 0.90          | 0.53           | 0.23               | 1.32                |
| Base LSTM       | 0.85          | 0.39           | 0.34               | 1.79                |
| **Average**     | **0.88**      | **0.58**       | **0.27**           | **1.18**            |

Table 2: Aggregated results for the various language families. We provide the performance averaged across all systems, and in parenthesis the performance of the best system per family. The best system is identifiable in subscript: C - CULing, T - Base trm-single, D - DeepSpin-02. We include here only families with at least 3 languages in the data.

| Split            | Accuracy Form | Accuracy Lemma | Edits Distance Form | Edits Distance Lemma |
|------------------|---------------|----------------|---------------------|----------------------|
| Afro-Asiatic     | 0.93 (0.93)   | 0.51 (0.80)   | 0.53 (0.74)         | 0.89 (0.90)          |
| Austronesian     | 0.78 (0.82)   | 0.45 (0.70)   | 0.63 (0.74)         | 1.02 (0.90)          |
| Germanic         | 0.86 (0.88)   | 0.63 (0.74)   | 0.55 (0.86)         | 1.32 (0.90)          |
| Indo-Iranian     | 0.93 (0.97)   | 0.55 (0.86)   | 0.56 (0.90)         | 1.32 (0.90)          |
| Niger-Congo      | 0.95 (0.98)   | 0.69 (0.86)   | 0.60 (0.60)         | 1.32 (0.90)          |
| Oto-Manguean     | 0.84 (0.86)   | 0.64 (0.89)   | 0.60 (0.60)         | 1.32 (0.90)          |
| Romance          | 0.97 (0.99)   | 0.69 (0.86)   | 0.60 (0.60)         | 1.32 (0.90)          |
| Turkic           | 0.95 (0.96)   | 0.64 (0.89)   | 0.60 (0.60)         | 1.32 (0.90)          |
| Uralic           | 0.88 (0.90)   | 0.65 (0.72)   | 0.60 (0.60)         | 1.32 (0.90)          |

### 4 Experiments

In order to better assess the difficulty of morphological inflection, we compare the performances of 3 of the top-ranked system at task 0 (inflection) of SIGMORPHON’s 2020 shared-task. We examined each system on both the the standard (form) split and the novel (lemma) split.

When re-splitting, we kept the same proportions of the form-split data, i.e. we split the inflection tables 70%, 10% and 20% for the train, development and test set. In terms of examples the proportions may vary as not all tables are of equal size. In practice, the averaged train set size in examples terms was only 3.5% smaller in the lemma-split data, on average. The split was done randomly as is standard in SIGMORPHON tasks, although frequency-based sampling is also conceivable and is sometimes used, as in Cotterell et al. (2018).

#### 4.1 The Languages

SIGMORPHON’s 2020 shared-task includes datasets for 90 typologically and genealogically diverse languages from 14 language families. The languages are varied along almost any typological dimension, from fusional to agglutinative, small inflection tables to vast ones. They include mostly prefixing and mostly suffixing languages with representation of infixing and circumfixing as well. The languages vary also in use, including widely-used languages such as English and Hindi and moribund or extinct languages like Dakota and Middle High German.

#### 4.2 The Models

We tested the effects of lemma-splitting on our own LSTM-based model as well as 3 of the 4 top-ranked systems in the shared task.

**Base LSTM** We implemented a character-based sequence-to-sequence model which consists of a 1-layer bi-directional LSTM Encoder and a 1-layer unidirectional LSTM Decoder with a global soft attention layer (Bahdanau et al., 2014). Our model was trained for 50 epochs with no model selection.

**Base trm-single** The shared-task’s organizers supplied various baselines, some based on a transformer architecture that was adapted for character-level tasks (Wu et al., 2021). All baseline models include 4 encoder and 4 decoder layers, consisting of a multi-head self-attention layer and 2 feed-forward layers, equipped with a skip-connection. In every decoder layer a multi-head attention layer attends to the encoder’s outputs. The network was trained for 4,000 warm-up steps and up to 20,000 more steps, each step over a batch of size 400. The model was examined with and without augmented data, trained separately on each language or each language family. One of the baseline setups, training a model per language without augmented data, made it to the top 4 systems and we include it here.

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The best performing system, UIUC (Canby et al., 2020), did not have a publicly available implementation.

The code is available at https://github.com/shijie-wu/neural-transducer.

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The full list with the originally released data are at https://github.com/sigmorphon2020/task0-data.

The code is available at https://github.com/OnlpLab/LemmaSplitting.

The code is available at https://github.com/shijie-wu/neural-transducer.
**DeepSpin** Peters and Martins (2020) submitted a recurrent neural network – dubbed DeepSpin-02.\(^{10}\) The system is composed of 2 bi-directional LSTM encoders with bi-linear gated Attention (Luong et al., 2015), one for the lemma characters and one for the features characters, and a unidirectional LSTM Decoder for generating the outputs. The innovation in the architecture is the use of sparsemax (Martins and Astudillo, 2016) instead of softmax in the attention layer.\(^{11}\)

**CULing** Liu and Hulden (2020)’s system is also based on the transformer architecture, with hyperparameters very similar to base trm-single.\(^{12}\) Their innovation is in restructuring the data such that the model learns to inflect from any given cell in the inflection table rather than solely from the lemma.

### 4.3 Results

Table 1 summarizes our main results. We clearly see a drop in the performance for all systems, with an average of 30 points. The table also shows that splitting the data according to lemmas allows discerning between systems that appear to perform quite similarly on the form-split data. The best system on the lemma-split data, DeepSpin-02, outperforms the second-ranked CULing system by about 13 points with both baseline systems performing significantly worse. The results in terms of averaged edit distance show the same trends.

DeepSpin-02 emerges victorious also in Table 2, where results are broken down by language family. The table shows that DeepSpin-02 is the best performer over all language families when data is lemma-split, in contrast to the mixed picture over the form-split data.

The average performance per language family seems to be controlled by training data availability. For example, Germanic languages show average drop of 23 points, while for Niger-Congo languages the drop is 39 points on average.

In order to further examine the relation between the amount of training data and drop in performance we plotted in Figure 1 the drop per system and per language against the size of the available train data, color-coded to indicate systems. It shows that the major drops in performance that contributed the most to the overall gap between the splits are in those low-resourced language. Remarkably, for some systems and languages the drop can be as high as 95 points. On the other hand, on high-resourced languages with 40,000 training examples or more, all systems didn’t lose much. The analysis also shows the advantage of DeepSpin-02 in the lower-resourced settings that made it the best performer overall.

When color-coding the same broken-down data for linguistic family membership rather than system, as we do in Figure 2, it becomes clear that there is no evidence for specific families being eas-

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\(^{10}\)The code is available at https://github.com/deep-spin/sigmorphon-seq2seq.

\(^{11}\)The system submitted as DeepSpin-01 uses 1.5-entmax (Peters and Martins, 2019) rather than sparsemax. Both systems perform highly similarly, hence we do not detail results for both.

\(^{12}\)The code is available at https://github.com/LINGuistLIU/principal_parts_for_inflection.
ier for inflection when little data is provided. The figure does show the remarkable discrepancy in annotation effort, as the high-resourced languages mostly belong to 2 families: Germanic and Uralic.

5 Discussion

We proposed a method for splitting morphological datasets such that there is no lemma overlap between the splits. On the re-split of SIGMORPHON’s 2020 shared-task data, we showed that all top-ranked systems suffer significant drops in performance. The new split examines models’ generalization abilities in conditions more similar to their desired usage in the wild and allows better discerning between the systems in order to point to more promising directions for future research — more so than the original form-split data on which all systems fared similarly. The suggested move to a harder split is not unlike many other NLP tasks, in which challenging splits are suggested to drive the field forward. We thus call for morphological studies to carefully attend to the data used and expose the actual difficulties in modelling morphology, in future research and future shared tasks.

Acknowledgements

This research was funded by the European Research Council under the European Union’s Horizon 2020 research and innovation programme, (grant agreement No. 677352) and by a research grant from the ministry of Science and Technology (MOST) of the Israeli Government, for which we are grateful.

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