Morphological Reinflection with Multiple Arguments: An Extended Annotation schema and a Georgian Case Study

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Abstract

In recent years, a flurry of morphological datasets had emerged, most notably UniMorph, a multi-lingual repository of inflection tables. However, the flat structure of the current morphological annotation schema makes the treatment of some languages quirky, if not impossible, specifically in cases of polypersonal agreement, where verbs agree with multiple arguments using true affixes. In this paper, we propose to address this phenomenon by expanding the UniMorph annotation schema to a hierarchical feature structure that naturally accommodates complex argument marking. We apply this extended schema to one such language, Georgian, and provide a human-verified, accurate and balanced morphological dataset for Georgian verbs. The dataset has 4 times more tables and 6 times more verb forms compared to the existing UniMorph dataset, covering all possible variants of argument marking, demonstrating the adequacy of our proposed scheme. Experiments with a standard reinflection model show that generalization is easy when the data is split at the form level, but extremely hard when splitting along lemma lines. Expanding the other languages in UniMorph to this schema is expected to improve both the coverage, consistency and interpretability of this benchmark.

1 Introduction

In recent years, morphological (re)inflection tasks have gained a lot of attention in NLP.\footnote{Cf. the series of SIGMORPHON shared tasks: https://sigmorphon.github.io/sharedtasks/} Subsequently, several multi-lingual morphological datasets have emerged to allow for the supervised training of morphological models, most notably UniMorph (McCarthy et al., 2020), that organizes words into inflectional tables, annotating each inflected word-form with its respective feature-set.

While western languages are widely represented in UniMorph, many morphologically rich languages (Tsarfaty et al., 2010, 2020) exhibit rich and diverse inflection patterns that make them less compatible with the flat feature-sets in the UniMorph schema. Concretely, in some cases it is completely impossible to annotate parts of the inflectional paradigm with a flat bundle, as is the case with case stacking, and in other cases, such as polypersonal agreement, the annotation solutions provided are unnatural, non-transparent, and are barely used in practice. As a result, languages exhibiting such phenomena are under-represented in UniMorph, and when they are, the inflection tables for these languages are often incomplete.

In this paper we propose a general solution for annotating such structures, thus extending the UniMorph annotation schema to fully cover a wider range of morphologically-complex argument-marking phenomena. Following Anderson (1992), we propose a so-called layered annotation of features, where the inflectional features take the form of a hierarchical structure, in the spirit of formal linguistic frameworks as that of Johnson (1988); Pollard and Sag (1994); Shieber (2003); Bresnan et al. (2015). We organize the features of multiple arguments in a hierarchical structure, rather than the current flat structure that accommodates only subject concords. This schema shift allows for an adequate annotation of polypersonal agreement and of possessed nominals, where a word has multiple number and gender features, as well as forms with case stacking, where a word has multiple cases.

We apply the suggested solution to Georgian, an agglutinative language with a convoluted verbal system, that indicates both subjects and objects with true affixes (rather than clitics that are omissible from the inflection tables). We create a new human-verified dataset for Georgian, that covers most of the grammatical phenomena in Georgian verbs, and includes 118 lemmas, adding up to about 21k verb forms, compared with the 47 lemmas and 3.3k verb forms, some of which are erroneous, cur-
Table 1: A typical Georgian verb. Note the 2 argument markers, object (tagged with O) and subject (S).

The crux of the matter is that in the current annotation schema, complex features assigned to additional arguments are treated as a single non-decomposable feature, that lack any internal structure, unlike the features of the main (so-called ‘internal’) argument, that are individually spelled out. We argue that the lack of transparency and usability are due to the misrepresentation of the inherently hierarchical and compositional structure of the features in such forms. We suggest to explicitly annotate these forms with features that are all explicitly composed of the same primitive features.

All in all, the lack of a sufficiently expressive annotation standard leads to a data distribution that is skewed, unrealistically simple, and, when language-specific annotation solutions are painfully needed, they suffer from inconsistencies and ad-hoc decisions. For these reasons, we set out to extend the

ture set includes at most one pronominal feature bundle (i.e., person-gender-number).

However, this assumption does not apply to verbs with object concords, as exhibited in Georgian (see Table 1), Inuit and many Bantu languages inter alia, nor does it apply to possessed nouns that mark the features of both the possessor and the possessee. Examples (1a)–(1d) illustrate this:

(1) a. Georgian: *gagišvebt* ‘We will let you(sg.) go’ (SUBJ-1PL, OBJ-2SG)
   b. Turkish: *kedisisin* ‘you are his cat’ (NOUN-SG, SUBJ-2SG, POSS-3SG)
   c. Swahili: *ninakupenda* ‘I love you’ (SUBJ-1SG, OBJ-2SG)
   d. Hebrew: *emdata* ‘her position’ (NOUN-SG, POSS-3SG-FEM)

The solution proposed in UniMorph to annotating these phenomena is via concatenating several properties into a single string, lacking any internal structure; e.g., ARGAC2S indicates a form with a 2nd person singular accusative argument (Sylak-Glassman, 2016). However, there are at least two shortcomings to this solution. First, it is not sufficiently transparent. ARGAC2S is an opaque string, that does not decompose into the known features licensed by the UniMorph features list (i.e., ACC, 2, SG). Secondly, and possibly due to this lack of transparency, this annotation hack is hardly ever used in practice. Hence, from all examples in (1), only the Hebrew form is included in UniMorph, and tagged as N;SG;FEM;PSS3S with multiple possessor features merged into the flat string PSS3S.

The Russian lemma *LETET1b*: reinflecting from (PRS;1;SG,пету) to (IMP;2;SG,лети) will be represented as:

\[
\text{(PRS;1;SG,пету), (IMP;2;SG,___) \mapsto \text{лети}}
\]

Standardly, the data for training morphological models (e.g., Wu et al., 2020; Makarov and Clematide, 2018) is taken from UniMorph (McCarthy et al., 2020), a multilingual morphological dataset in which words are grouped by lemma into inflection tables, each word is tagged with an un-ordered set of morphological features. The features list is shared across languages. The inflection tables are meant to be exhaustive, i.e., covering all possible forms of a lemma, regardless of usability.

Although the features were designed to apply cross-lingually, some blind-spots exist. Most relevant to our work is the assumption that every fea-
UniMorph annotation schema to accommodate all such cases and to enable a proper coverage of languages, such as Georgian and many others.

3 The Proposed Schema

We propose to extend the UniMorph annotation schema to cover multiple pronominal feature-bundles in the same word-form, via a layering approach, originally proposed for morphological systems by Anderson (1992). Anderson suggests to arrange the morphosyntactic representation (MSR) of words in a hierarchy (dubbed layers) of features, in the sense that every element of the unordered set of features can be composed of another unordered set of features. That is, a general feature annotation looks as in (2a). A specific transitive verb annotation could be as depicted in (2b):

(2) a. \[[f_1, f_2, \ldots, [F_i : f_{i1}, f_{i2}, \ldots [F_j : f_{j1} \ldots]]]\]

b. \[[V, \text{Tense},\]
\[\text{[nom : Per, Num, Gen]},\]
\[\text{[acc : Per, Num, Gen]}\]]

This hierarchical feature structure is reminiscent of unification grammars or attribute-value grammars (Shieber, 2003; Johnson, 1988) that are extensively used in syntactic theories such as GPSG, HPSG, and resemble the f-structures in LFG (Gazdar et al., 1989; Pollard and Sag, 1994; Bresnan et al., 2015).

Here we employ these structures to organize the features of morphologically-marked arguments hierarchically, so an argument is characterized by a feature composite of all features pertaining to that argument. That is, each argument’s feature-bundle os specifically marked with the argument it belongs to, and is decomposed into the primitive features licensed by the UniMorph scheme. It also homogeneously annotates the different kinds of arguments, in contrast with the current schema where the subject features are assigned to the verb directly. Thus, the English form thinks previously annotated as V:PRS:3;SG will be annotated as V:PRS:NOM(3;SG). In languages that mark multiple arguments, different kinds of arguments can be marked with their feature-bundles without conflicts. The proposed schema thus facilitates the annotation of the poorly-treated or untreated phenomena as illustrated in (1). These are, respectively:

(3) a. Georgian: gagišvebt ‘We will let you go’
V:FUT:NOM(1;PL);ACC(2;SG)

b. Turkish: kedisisin ‘you are his cat’
N;SG:NOM(2;SG);POSS(3;SG)

c. Swahili: ninakupenda ‘I love you’
V:PRS:NOM(1;SG);ACC(2;SG)

d. Hebrew: emdata ‘her position’
N:SG:POSS(3;SG;FEM)

Table 2 compares the annotation of these examples in the current UniMorph schema compared with our proposed annotation schema. The hierarchical structures, beyond being more transparent, opens the door further for future study on compositional generalization in morphology.

The resemblance of our proposed schema to ideas in other fields of theoretical linguistics, most prominently to the f-structure in LFG (Bresnan et al., 2015) and to the nested Attribute-Value matrices in HPSG (Pollard and Sag, 1994), points to a natural interface with further syntactic and semantic annotations downstream.

4 A Case Study from Georgian

Linguistic Background Georgian is an agglutinative language with a verbal system that makes a vast use of affixes to convey a wide array of meanings, both inflectional and derivational (see Table 1). The Georgian verbal paradigm is divided into 5 classes known as: transitive, intransitive, medial, indirect and stative (Hewitt, 1995). The verbs are inflected to reflect 12 Tense-Aspect-Mood (TAM) combinations (traditionally known as screeves) sorted into 4 series: present and future, aorist, perfective, and the imperative. Each series has its own morpho-syntactic characteristics, most notably split-ergativity is manifested in the aorist.

The characteristic most essential to this work is that Georgian verbs always agree on person and number with the direct and indirect objects, on top of the subject-verb agreement. The Georgian data in UniMorph follows the convention of including objects only in third person singular — thus failing to provide a comprehensive coverage of the word-forms that can be attested in the language.

Additional issues with the current morphological data in UniMorph for Georgian verbs are: sparsity, as it includes only 47 inflection tables; lack of diversity, as all table are from the transitive class; and lack of accuracy, as the data was produced automatically without verification by native speakers.

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2Although not explicitly shown here, annotation of case stacking is also possible with our approach, while non-hierarchical annotations do not account for such cases. For example, Korean 교사에게 is can be tagged as N;SG:NOM(DAT).
Table 2: Examples for word-forms with multiple argument agreements. On the left we present the flat structure currently employed in UniMorph. All examples save Hebrew are not included in the UniMorph inflection tables, presumably due to their lack of transparency. On the right we present our proposed hierarchical structure, which is more transparent, and also ammenable for compositional generalization.

| Language | Word | Flat Structure | Hierarchical Structure |
|----------|------|----------------|-----------------------|
| Georgian: gagisiwebt | Trans: ‘We will let you go’ | Args: SUBJ-1PL, OBJ-2SG | |
| Turkish: kedisisin | Trans: ‘you are his cat’ | Args: NOUN-SG, SUBJ-2SG, POSS-3SG | |
| Swahili: ninakupenda | Trans: ‘I love you’ | Args: SUBJ-1SG, OBJ-2SG | |
| Hebrew: emdata | Trans: ‘her position’ | Args: NOUN-SG, POSS-3SG-FEM | |

Data Annotation A key contribution of this work is the creation of a new dataset for Georgian that follows the layered annotation schema and addresses the other shortcomings just described. We selected a list of 118 verb lemmata from all different classes. Every verb was manually annotated with its stem, its thematic affix and principal parts, to automatically generate the full inflection tables. This automatic generation of Georgian verbs is prone to some errors, for instance, in accounting for idiosyncratic phonologically-conditioned stem changes. Hence, we ran our data through 3 native Georgian speakers to assert its correctness, or fix when needed. In cases where speakers were unsure we used a Georgian morphological analyzer (Doborjimidze and Lobzhanidze, 2012) for consultation. In cases of disagreement, we used a majority vote among the speakers. In cases where speakers were unsure we used a Georgian morphological analyzer (Doborjimidze and Lobzhanidze, 2012) for consultation. In cases of disagreement, we used a majority vote among the speakers. In cases of disagreement, we used a majority vote among the speakers.

Table 3 summarizes the statistics over our annotated data. In total, we produced 21,054 verb forms, of 118 lemmata. The data is quite evenly balanced across the classes, with more verbs drawn from the more frequent transitive class. For comparison, the current UniMorph data has fewer lemmas, 3,300 forms, and includes only verbs that are transitive.

5 Experiments To assess the usability of our dataset, we trained a standard reinflection model, the character-level LSTM of Silfverberg and Hulden (2018), on our data. We sampled from our data 2 datasets for training morphological reinflection models, containing train, validation and test sets in sizes 8k, 1k and 1k examples, respectively. Following Goldman et al. (2021), one dataset employed an easier form-split, i.e., no forms appear in both train and test, and the other with the more challenging lemma-split, where lemmas from train, dev and test are disjoint. To assess the generalization capacity we

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3We based the list of verbs on those whose inflection tables appear on Hewitt (1995) and added some commonly-used verbs suggested by native speakers.

4All our data is publicly available at https://github.com/Onlp/GeorgianMorphology.

5For hyper-parameters tuning see Appendix C.

6This is the splitting method used in SIGMORPHON’s shared tasks on reinflection (e.g., Cotterell et al., 2018).
Table 4: Accuracy (Acc, higher is better) and Average Edit Distance (Avg ED, lower is better) for morphological reinflection on different train-test combinations.

| Train Set | Test set | Form Split | Lemma Split |
|-----------|----------|------------|-------------|
| New       | New      | 94.9% 0.15 | 1.3% 4.66   |
| New       | Original | 84.7% 0.3  | 0.3% 4.39   |
| Original  | New      | 35.2% 1.36 | 0.0% 6.22   |
| Original  | Original | 99.3% 0.01 | 0.0% 6.13   |

We varied the sources of both the train and test sets. We report 2 evaluation metrics: accuracy over exact matches, and average edit distance from gold.

Results and Analysis Table 4 presents the model’s performance for all train-test combinations. It shows that the model’s performance on the new data (top line combination) is largely on par comparing to its performance over training and testing on UniMorph’s original data (bottom combination). However, the model generalizes poorly from the original partial data to the forms in our test set which reflect the entire Georgian inflectional system. Generalization from our data to UniMorph’s set is a lot better. The results also show that the splitting method is crucial for success of the model, as it inflects easily to unseen forms, but much harder when inflecting forms in a previously unseen lemma.

6 Conclusion

This paper proposes a transition of the UniMorph annotation standard to a layered hierarchical annotation of features. This revised schema caters for complex marking phenomena including multiple pronominal agreement. We apply it to Georgian, and construct a corresponding new dataset that is large, balanced, complete with respect to grammatical phenomena in the Georgian verb system and verified by native-speakers. Our experiments with a standard reinflection model on the old and new Georgian datasets shows that the old UniMorph dataset does not generalize well to the new test set, due to its partial coverage. This work is intended to encourage the community to extend the annotation of different languages to include phenomena such as polypersonal agreement and others that can be dealt with using a hierarchical annotation, ultimately leading to more complete and consistent benchmarks for studying non-trivial and less-explored areas of computational morphology.

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A Learning Curves

Fig. 1 exemplifies the sufficiency of our dataset for training an inflection model on form-split data as doubling the data amount from 4,000 to 8,000 yields relatively minor improvement. It also shows that for the lemma-split data, the model completely fails. It starts improve marginally with more than 2,000 examples, although its performance remains far from satisfactory. This leaves room for exploration of bootstrapping and augmentation methods or more sophisticated modeling to improve results.

![Graph showing learning curves for form-split and lemma-split data](image)

Figure 1: Inflection accuracy over form-split and lemma-split test sets as a function of train set size.

B Tech-Spec

All algorithms described in the paper were executed on a single machine equipped with one NVIDIA TITAN Xp GPU, 16 Intel i7-6900K(3.20GHz) CPUs and 126GB RAM. Since the LSTM algorithm was implemented on DyNet, there was no need of the GPU, and all the calculations were done using only the CPU.

C Hyper Parameters

1. Embedding size = 100
2. Hidden state size = 100
3. Attention size = 100
4. Number of LSTM layers = 1

During training, we experimented with several values for the hyper-parameters detailed above. However, for all the combinations we tried, the results barely changed both at the form-split setting and the lemma-split setting.