Exploring the State-of-the-Art Language Modeling Methods and Data Augmentation Techniques for Multilingual Clause-Level Morphology

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Abstract

This paper describes the KUIS-AI NLP team’s submission for the 1st Shared Task on Multilingual Clause-level Morphology (MRL2022). We present our work on all three parts of the shared task: inflection, reinflection, and analysis. We mainly explore two approaches: Transformer models in combination with data augmentation, and exploiting the state-of-the-art language modeling techniques for morphological analysis. Data augmentation leads a remarkable performance improvement for most of the languages in the inflection task. Prefix-tuning on pretrained mGPT model helps us to adapt reinflection and analysis tasks in a low-data setting. Additionally, we used pipeline architectures using publicly available open source lemmatization tools and monolingual BERT-based morphological feature classifiers for reinflection and analysis tasks, respectively. While Transformer architectures with data augmentation and pipeline architectures achieved the best results for inflection and reinflection tasks, pipelines and prefix-tuning on mGPT received the highest results for the analysis task. Our methods achieved the first place in each of the three tasks and outperforms mT5-baseline with 89% for inflection, 80% for reinflection and 12% for analysis. Our code is publicly available.

1 Introduction

The shared task on multilingual clause-level morphology was designed to provide a benchmark for morphological analysis and generation at the level of clauses for various typologically diverse languages. The shared task is composed of three subtasks: inflection, reinflection and analysis. For the inflection task, participants are required to generate an output clause, given a verbal lemma and a specific set of morphological tags (features) as an input. In the reinflection task the input is an inflected clause, accompanied by its features (tags). Participants need to predict the target word given a new set of tags (features). Finally, the analysis task requires predicting the underlying lemma and tags (features) given the clauses.

The shared task includes eight languages with different complexity and varying morphological characteristics: English, French, German, Hebrew, Russian, Spanish, Swahili, and Turkish.

In this work, we explored two main approaches: i) character-based Transformer architectures with data augmentation tricks, and ii) adapting recent tuning methods to language modeling for multilingual morphological tasks. Additionally, we have utilized pipeline architectures for reinflection and analysis tasks. For reinflection, we first identify the lemma of clause. Then, we use the top performing

| Task1: Inflection |
|-------------------|
| Source | Lemma | give |
| Features | IND;FUT;NOM(1,SG);ACC(3,SG,MASC);DAT(3,SG,FEM) |
| Target | Clause | I will give him to her |

| Task2: Reinflection |
|---------------------|
| Source | Clause | I will give him to her |
| Features | IND;FUT;NOM(1,SG);ACC(3,SG,MASC);DAT(3,SG,FEM) |
| Desired Features | IND;PRS;NOM(1,PL);ACC(2);DAT(3,PL);NEG |
| Target | Desired Clause | We don’t give you to them |

| Task3: Analysis |
|-----------------|
| Source | Clause | I will give him to her |
| Target | Lemma | give |
| Features | IND;FUT;NOM(1,SG);ACC(3,SG,MASC);DAT(3,SG,FEM) |

Table 1: Description of the each three task: inflection, reinflection, analysis. Task1 (Inflection). For the given lemma and the features, target is the desired clause. Task2 (Reinflection). Input is the clause, its features, and the desired output features. Target is the desired clause that represented by the desired features in the source. Task3 (Analysis). For a given clause, output is the corresponding lemma and the morphological features.
model for the inflection task to generate the target clause from it. For the analysis task, we carry out lemmatization and morphological tagging as separate tasks.

2 Methods

Our methods can be summarized as follows: training models with Transformer architectures Vaswani et al. (2017); Wu et al. (2021) for each task (2.1), prefix-tuning (Li and Liang, 2021) on the pretrained mGPT model (Shliazhko et al., 2022) for reinflection and analysis tasks (2.2), using data augmentation for inflection (2.3), and designing pipelines for reinflection and analysis (2.4).

2.1 Transformer & TagTransformer

Vanilla Transformer. We used a smaller version of a vanilla Transformer architecture that contains 4 layers of encoder and decoder with 4 multi-head attentions. The embedding size and the feed-forward dimension is set to 256 and 1024, respectively.

TagTransformer. Following Wu et al. (2021), we used special positional encodings and type embeddings in the encoder part of the vanilla Transformer. These special encodings count the positions of the characters in positional encoding and set all the features to zero. It overcomes the issue of different distances between a specific character and a set of morphological features. It also adds a special token to make distinctions between a feature and a character. Also, we have used layer normalization before the self-attention and feed-forward layers of the network that leads to slightly better results.

2.2 Prefix-Tuning

Using prefix-tuning reduces computational costs by optimizing a small continuous task-specific vectors, called prefixes, while keeping frozen all the other parameters of the LLM as a conditional generation tasks. We have added two prefixes at the beginning of the each layer and the gradient optimization made across these prefixes that is described in the Figure 1. It outperforms the fine-tuning methods in low-data resource settings and better adapts to unseen topics during prompt training as Li and Liang (2021) showed. Additionally, this method can be applied both for auto-regressive (GPT-based) and sequence-to-sequence (BART-based) architectures.

2.3 Data augmentations

Hallucinating the data for low-resource languages results with a remarkable performance increase for inflection Anastasopoulos and Neubig (2019). The hallucinated data is generated by replacing the stem characters of the aligned word with random characters by using the validation or test sets like in Figure 2. This way, the increase in the training data helps the model to learn and generalize rare seen samples, properly. On the other hand, the amount of data that will be hallucinated and added to the training data (hyperparameter $N$), is also another parameter that affects the accuracy which needs to be decided for each language according to its complexity and topology. Therefore, the hyperparameter $N$ is selected according to our specific observations for each language after a grid search.

We used a simple method to handle modelling of compound verbs for Turkish models. For all compound verbs, the space token between the constituent verbs was replaced with an underscore to ken both in input and target clauses. The replacement was done automatically by detecting compound verbs using POS tagging of clauses.

2.4 Pipelines

Reinflection Pipeline For German and French we design a pipeline as follows: first, the lemma for the input clause is extracted using an external lemmatizer, and then the respective best performing model for the Inflection task is used to generate the target clause. For German, we have used the ParZu Dependency Parser (Sennrich et al., 2009, 2013) to handle both lemmatization and separable verbs. For French, we have used the spaCy pipeline (Honnibal et al., 2020). Both for German and French, we additionally handled clauses involving auxiliary verbs.

Analysis Pipeline For German, French, and Russian the task was split into two parts: lemmatization
and morphological tagging. For the lemmatization part, we have used the ParZu Dependency Parser for German, and spaCy pipelines for French and Russian. For the morphological tagging subtask in the analysis task, we have trained simple linear classifiers on top of BERT/RoBERTa embeddings of the input clause. For German, we have used the base cased BERT model from HuggingFace (Chan et al., 2020); for French, we have used the CamemBERT base cased model from HuggingFace (Martin et al., 2020); and for Russian, we have used the pre-trained base cased RuBERT model from DeepPavlov.AI (Kuratov and Arkhipov, 2019).

3 Experimental Settings

3.1 Dataset

There are eight languages with varying linguistic complexity that comes from different language families: English, French, German, Hebrew, Russian, Swahili, Spanish, Turkish. For Hebrew there are two versions as Hebrew-vocalized and Hebrew-unvocalized.

For each language in each three tasks as described before; there is one training set, one development set, and one test set which does not have labels. Training data for each language contains 10,000 instances, and there are 1,000 samples in development and test sets. However, Swahili and Spanish are surprise languages that announced two weeks before the final submission day, together with the unlabeled test data for each language.

3.2 Evaluation

Models are evaluated according to Exact Match (EM), Edit Distance (ED), and F1 accuracy. For task1 (inflection) and task2 (reinflection) ED is the leaderboard metric. On the other hand, F1 score is the leaderboard metric for task3 (analysis).

EM accuracy represents the ratio of correctly predicted lemma and features, and ED is calculated based on Levenshtein Distance which indicates how different two strings are, (the ground truth and prediction for our case) from each other. F1 accuracy is the harmonic mean of the precision and recall. F1 accuracy is upweighted for the lemma score in our task. In the leaderboard, the results are averaged across each language.

3.3 Shared Tasks

3.3.1 Task1: Inflection

We have achieved the best results by using either a vanilla Transformer architecture or TagTransformer. Data hallucination method improved our results significantly, except for Russian and Spanish. It decreased our accuracy both for EM and ED accuracy in Russian and Spanish, so, we did not apply any augmentation techniques for these languages. We have achieved the best performances with \( N=5,000 \) hallucinated data for German, French, Hebrew/Hebrew-unvoc, Swahili, and \( N=2,500, N=1,000 \) for English and Turkish, respectively.

As suggested in Wu et al. (2021), we examined the effect of the large batch sizes that results with an increase in accuracy. Thus, we set the batch size to 400 and we trained our models for 20 epochs. We used Adam optimizer by setting \( \beta_1 \) to 0.9 and \( \beta_2 \) to 0.98. We started with a learning rate of 0.001 and linearly increase it with 4,000 warm-up steps. Then, we decrease it with the inverse of the square-root for the remaining steps. We have used label smoothing with a factor of 0.1 and applied the same dropout rate of 0.3.

3.3.2 Task2: Reinflection

For all the models that we used for reinflection task; we tried both (i) giving the all source data as input, and (ii) using only the inflected clause and its desired features. We have examined that, both our EM and ED accuracy increased when we
| Task1: Inflection | Task2: Reinflection | Task3: Analysis |
|-------------------|---------------------|-----------------|
| **Deu** | Transformer + Hall (N=5000) | Pipeline |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 89.43 ± 0.011 | 0.464 ± 0.025 | 88.50 | 0.464 | 95.90 |
| **Eng** | Transformer + Hall (N=2500) | Prefix-Tuning |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 97.13 ± 0.006 | 0.118 ± 0.008 | 95.23 ± 0.016 | 0.126 ± 0.035 | 99.21 ± 0.013 |
| **Fra** | Transformer + Hall (N=5000) | Pipeline |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 93.43 ± 0.002 | 0.202 ± 0.056 | 92.20 | 0.327 | 97.90 |
| **Heb** | Transformer + Hall (N=5000) | Transformer |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 95.67 ± 0.005 | 0.135 ± 0.017 | 84.25 ± 0.036 | 0.800 ± 0.301 | 95.37 ± 0.014 |
| **Heb-unvoc** | Transformer + Hall (N=5000) | TagTransformer |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 92.77 ± 0.002 | 0.288 ± 0.015 | 65.50 ± 0.023 | 0.923 ± 0.019 | 86.00 ± 0.014 |
| **Rus** | Transformer + Hall (N=5000) | Transformer |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 92.23 ± 0.005 | 0.912 ± 0.129 | 89.23 ± 0.012 | 0.985 ± 0.020 | 95.50 |
| **Swa** | Transformer + Hall (N=5000) | Transformer |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 97.70 ± 0 | 0.039 ± 0.001 | 74.20 ± 0.024 | 0.391 ± 0.024 | 85.79 ± 0.009 |
| **Spa** | Transformer | Transformer |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 94.13 ± 0.005 | 0.227 ± 0.024 | 75.77 ± 0.022 | 0.547 ± 0.044 | 95.90 ± 0.008 |
| **Tur** | TagTransformer + Hall (N=1000) | TagTransformer |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 99.90 ± 0 | 0.001 ± 0 | 68.90 ± 0.025 | 0.849 ± 0.099 | 94.56 ± 0.012 |
| **Average** | | | | |
| EM↑ | ED↓ | EM↑ | ED↓ | F1↑ |
| 94.71 ± 0.004 | 0.265 ± 0.030 | 81.53 ± 0.022 | 0.601 ± 0.077 | 94.01 ± 0.048 |

Table 2: Development results for all tasks and languages with the corresponding models. **Task1: Inflection** and **Task2: Reinflection** objectives are Exact Match (EM) and Edit Distance (ED), and F1 score for **Task3: Analysis**. Results are averaged over 3 runs and the official shared MRL2022 evaluation script was used to get the exact results.
ignore source clause’s features. We used the same vanilla Transformer architecture for Hebrew, Russian, Swahili, and Spanish and the same TagTransformer model for Heb-unvoc and Turkish. All the training parameters are exactly the same with ones that are described in the Inflection part.

For the LLM tuning approach, we have used a conditional generation procedure based on the prefix-tuning method described in Li and Liang (2021), only for English. The source and target are given together with the trainable prefixes, i.e. continuous prompt vectors, and the gradient optimization made across these prefixes. For the mGPT-based Prefix-Tuning model, we have used the Huggingface, Wolf et al. (2019) and the corresponding model weights sberbank-ai/mGPT. The prefixes were trained for 7 epochs with a batch size of 5. We used Adam optimizer with weight decay fix which is introduced in Loshchilov and Hutter (2017) with $\beta_1=0.9$ and $\beta_2=0.999$. The learning rate is initialized to $5 \times 10^{-5}$ and a linear scheduler is used without any warm-up steps.

### 3.3.3 Task3: Analysis

We have used the prefix-tuning method, again for analysis, because of its success in the low-level source of data: English, Swahili, Spanish and Turkish compared to other LMs. The prefix template was given as the source and the features were masked. Vanilla Transformer model was used for Hebrew and unvocalized Hebrew. The clause-level input was given and target lemma together with its features were expected from the output like a machine translation task. mGPT prefix tuning was done for 10 epochs and all other training parameters identical for the ones used in reinflection task. Also, Transformer training parameters are identical to the ones used in reinflection task.

For morphological tagging, the classifier models have 2 linear layers of size matching the LLM’s embedding dimensions with drop-out layers in between with a drop-out rate of 0.2, followed by a ReLU activation. The mean of the cross entropy losses for all morphological features (tags) was taken as the loss. All classifiers were trained for 20 epochs.

### 3.4 Results

Our development results for each task and language are provided in Table 2. The announced results by the shared task are in the Table 3 which are evaluated among the provided unlabeled test set.

| Model        | Inflection | Reinflection | Analysis |
|--------------|------------|--------------|----------|
| Transformer Baseline | 3.278      | 4.642        | 0.800    |
| mT5 Baseline | 2.577      | 2.826        | 0.845    |
| KUIS-AI      | 0.266      | 0.560        | 0.950    |

Table 3: Submitted results for MRL shared task that is averaged across 9 languages. Metrics for the inflection and reinflection tasks is the edit distance, and for analysis the metric is averaged F1 score with the lemma being treated as an up-weighted feature.

In task1, the vanilla Transformer mostly beats TagTransformer except for Turkish. TagTransformer’s special embeddings work surprisingly well for Turkish and it achieves 99.9% EM accuracy and 0.001 ED on development data, which is almost perfect. For Task2, the vanilla Transformer works better since it achieved the best results across 4 languages. Our pipeline increased our results compared to transformer models for German and French. On the other hand, the prefix-tuning method works well for English with mGPT. Finally, in task3, prefix-tuning achieves the best results for four different languages. Again, it achieves a remarkable accuracy score for English. On the other hand, our pipeline gives promising results for German, French, and Russian. Vanilla Transformer works quite well for Hebrew, but it still needs to be improved for Hebrew-unvocalized case.

When we look the Table 2 in row-vise for each language, our pipelines beat other models for German and French. Prefix-tuning is the winner model for English across each task. Transformer achieved the best results for Hebrew, Hebrew-unvoc, Russian, Swahili, Spanish and TagTransformer is the most successful model for Turkish.

### 4 Related Work

Word-level morphological tasks have been studied to a great extent, with LSTM (Wu and Cotterell, 2019; Cotterell et al., 2016; Malaviya et al., 2019; Sahin and Steedman, 2018), GRU (Conforti et al., 2018), variants of Transformer Vaswani et al. (2017); Wu et al. (2021) and other neural models (e.g., invertible neural networks (Sahin and Gurevych, 2020)). Unlike word-level, there is limited work on clause-level morpho-syntactic modeling. Goldman and Tsarfaty (2022) presents a new dataset for clause-level morphology covering 4 typologically-different languages (English, German, Turkish, and Hebrew); motivates redefining
the problem at the clause-level to enable the cross-linguistical study of neural morphological modeling; and derives clause-level inflection, reinflection, and analysis tasks together with baseline model results.

Pre-trained LLMs have been successfully applied to downstream tasks like sentiment analysis, question answering, named entity recognition, and part-of-speech (POS) tagging (Devlin et al., 2019; Yang et al., 2019; Raffel et al., 2020). Even though, there is limited work on applications of LLMs to morphological tasks, it has been demonstrated that using pretrained contextualized word embeddings can significantly improve the performance of models for downstream morphological tasks. Inoue et al. (2022) explored BERT-based classifiers for training morphosyntactic tagging models for Arabic and its dialect. Anastasyev (2020) explored the usage of ELMo and BERT embeddings to improve the performance of joint morpho-syntactic parser for Russian. Hofmann et al. (2020) used a fine-tuning approach to BERT for the derivational morphology generation task. Finally, Seker et al. (2022) presented a large pre-trained language model for Modern Hebrew that shows promising results at several tasks.

On the other hand, since fine-tuning LLMs requires to modify and store all the parameters in a LM that results with a huge computational cost, Rebuffi et al. (2017); Houlsby et al. (2019) used adapter-tuning which adds task-specific layers (adapters) between the each layer of a pre-trained language model and tunes only the 2%-4% parameters of a LM. Similarly, Li and Liang (2021) proposed prefix-tuning which is a light-weight alternative method for adapter-tuning that is inspired by prompting.

5 Conclusion

In this paper, we have adapted the state-of-the-art methods in language modeling into multilingual clause-level morphology tasks: inflection, reinflection, and analysis. Due to the different complexity between tasks and the varying morphological characteristics of languages, there is no single best model that achieves the best results for each task in each language. Thus, we have implemented different types of models with different objectives. On average, we have achieved the best results for every three tasks among all participants.

For inflection, the vanilla Transformer and TagTransformer model with special embeddings achieve the best results, and data hallucination substantially improves accuracy. However, the hyperparameter $N$ (the number of hallucinated samples) has a crucial role in the accuracy and should be selected carefully for each language.

The reinflection task is more challenging compared to the other tasks due to its complex input form. To overcome this issue, we have removed the original feature tags from the input. We only used the inflected clause and target features in the input. We used mGPT-based prefix-tuning for English, vanilla Transformer for Hebrew, Russian, Swahili, Spanish, and TagTransformer for Hebrew-unvocalized and Turkish as our models. We also followed a pipeline to reduce the reinflection task to the inflection task by running lemmatization on the input clause and inference. We have used the top-performing model for the inflection tasks on the lemma for German and French for that.

Finally, for the analysis task, we have used a vanilla Transformer for Hebrew and Hebrew-unvocalized, prefix-tuning method for English, Swahili, Spanish and Turkish. We also designed a pipeline using external lemmatization tools and morphological feature classifiers using pre-trained LM embeddings for German, French, and Russian as our models.

Acknowledgements

This work is supported by KUIS-AI Center from Koç University, Istanbul. We gratefully acknowledge this support. Also, special thanks to Betül Özates for the help for Turkish dependency parser. Last but not least, we would like to kindly thank our organizers for answering our questions and for the effort they have made to fix the issues that we struggled with during the competition.

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