

# NEURAL GRAPHEME-TO-PHONEME CONVERSION WITH PRE-TRAINED GRAPHEME MODELS

Lu Dong<sup>1\*</sup>, Zhi-Qiang Guo<sup>1</sup>, Chao-Hong Tan<sup>1</sup>, Ya-Jun Hu<sup>2</sup>, Yuan Jiang<sup>1,2</sup>, Zhen-Hua Ling<sup>1</sup>

<sup>1</sup>National Engineering Laboratory for Speech and Language Information Processing,  
University of Science and Technology of China, Hefei, P. R. China

<sup>2</sup>iFLYTEK Research, iFLYTEK Co., Ltd., Hefei, P. R. China

{dl1111, gzq, chtan}@mail.ustc.edu.cn, {yjhu, yuanjiang}@iflytek.com, zhling@ustc.edu.cn

## ABSTRACT

Neural network models have achieved state-of-the-art performance on grapheme-to-phoneme (G2P) conversion. However, their performance relies on large-scale pronunciation dictionaries, which may not be available for a lot of languages. Inspired by the success of the pre-trained language model BERT, this paper proposes a pre-trained grapheme model called grapheme BERT (GBERT), which is built by self-supervised training on a large, language-specific word list with only grapheme information. Furthermore, two approaches are developed to incorporate GBERT into the state-of-the-art Transformer-based G2P model, i.e., fine-tuning GBERT or fusing GBERT into the Transformer model by attention. Experimental results on the Dutch, Serbo-Croatian, Bulgarian and Korean datasets of the SIGMORPHON 2021 G2P task confirm the effectiveness of our GBERT-based G2P models under both medium-resource and low-resource data conditions.

**Index Terms**— grapheme-to-phoneme conversion, pre-trained grapheme model, self-supervised training, Transformer

## 1. INTRODUCTION

The grapheme-to-phoneme (G2P) conversion task is predicting the pronunciation of words from their spellings. Considering that a pronunciation dictionary can never cover all possible words in a language, G2P conversion is essential for any applications that depend on the mapping relationship between the spoken and written forms of a language, such as TTS and ASR [1, 2, 3].

Many studies have been conducted on G2P conversion. In early years, joint n-gram models [4], joint sequence models [5] and wFST [6] were proposed. Recently, neural networks such as LSTM [7] and Transformer [8] have showed powerful ability on G2P conversion. The Transformer-based models have achieved state-of-the-art performance in many benchmarks [8, 9]. Some imitation learning based methods [10] also achieved comparable performance to the Transformer model. Nevertheless, building neural G2P models usually relies on a large, language-specific pronunciation dictionary, which may not be available for a lot of languages. One approach to address this issue is cross-lingual modeling. An early work is a wFST-based system [11]. Subsequently, multilingual neural networks [12] and pre-trained G2P models of high-resource languages [13] showed better cross-lingual G2P modeling ability. Another approach is utilizing multimodal data. Route et al. [14] found that additional audio supervision can help the G2P model to learn a

more optimal intermediate representation of graphemes. However, these studies mainly focused on utilizing the data resources of other languages or other modals to improve the performance of limited-resource G2P conversion, which do not explore better grapheme representations for G2P in an unsupervised way.

Therefore, this paper proposes a pre-trained grapheme model named grapheme BERT (GBERT) to improve the Transformer-based G2P model. The design of GBERT is inspired by the language model BERT [15], which provides contextual word representations and has achieved great successes in various NLP tasks, such as machine translation [16] and text summarization [17]. Similarly, GBERT is designed to capture the contextual relationship among the graphemes in a word, which is essential for the G2P task since the same grapheme may have different pronunciations due to different contexts. Following BERT, GBERT is a multi-layer Transformer encoder and is pre-trained by self-supervised learning on a large, language-specific word list with only grapheme information. The pre-training task of GBERT is a masked grapheme prediction task, i.e., predicting the masked graphemes from the seen graphemes in a word. Furthermore, two approaches are developed to improve the Transformer-based G2P model with GBERT. They are fine-tuning GBERT and fusing GBERT into the Transformer model by attention [16]. Experiments were conducted on the Dutch, Serbo-Croatian, Bulgarian and Korean datasets of the SIGMORPHON 2021 G2P task [18]. The results show that fusing GBERT by attention can reduce the word error rate (WER) and phone error rate (PER) of G2P under a medium-resource condition, while fine-tuning GBERT is effective for most languages under a low-resource condition. It should be noted that a concurrent work T5G2P [19] also mentions the pre-trained grapheme model can help the G2P conversion. The difference is that the T5G2P uses an encoder-decoder framework which captures contextual relationship between graphemes and autoregressive information of graphemes in the pre-training stage and only uses a directly fine-tuning method.

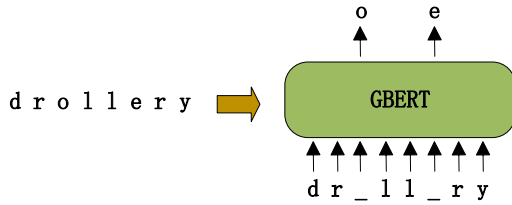
## 2. PROPOSED METHOD

In this section, we first introduce our proposed pre-trained grapheme model GBERT in Section 2.1. Then, we show the details of fine-tuning GBERT for G2P in Section 2.2 and the details of fusing GBERT into the Transformer-based G2P model [16] in Section 2.3.

### 2.1. Grapheme BERT (GBERT)

Following BERT [15], the model architecture of GBERT is a multi-layer bidirectional Transformer encoder where each input token can

\*Work done during internship at iFLYTEK Research.



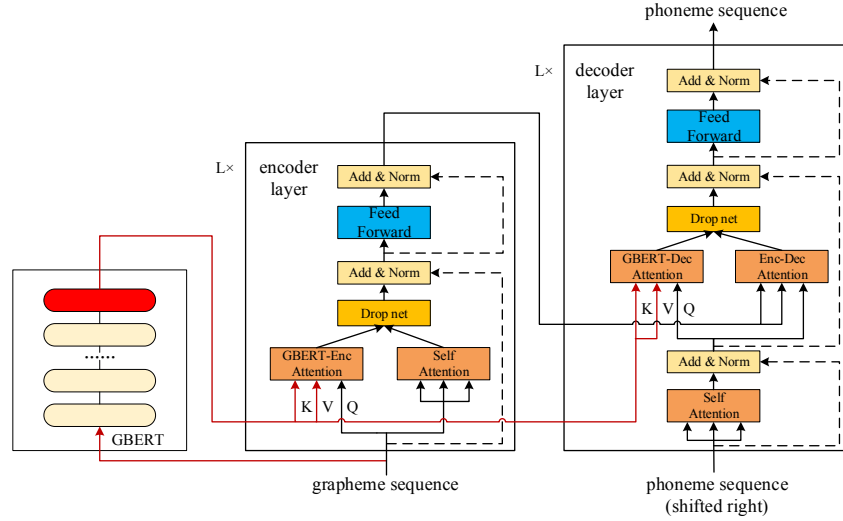
**Fig. 1.** The masked grapheme prediction task for pre-training GBERT. Here is an example of the English word *drollery*. The “\_” denotes the mask token.

see all input tokens. GBERT differs from BERT in that the input to GBERT is the grapheme sequence in a single word while the input to BERT is the wordpiece sequence in a single sentence or two sentences. The two-sentence input of BERT is designed to cope with the downstream tasks based on sentence pairs. However, this paper focuses on the single-word G2P task and thus we only consider the grapheme sequences in single words.

GBERT is pre-trained using a masked grapheme prediction task, i.e., masking some percentage of the input graphemes at random and predicting those masked graphemes from the seen ones. An illustration is shown in Fig. 1. These mask inputs (“\_”) are replaced by mask tokens (80% of the ratio), random graphemes (10% of the ratio) or original graphemes (10% of the ratio) to eliminate the mismatch between the pre-training task and the downstream G2P task, i.e., the mask tokens will not be encountered in the G2P task.

## 2.2. Fine-tuning GBERT for G2P Conversion

Fine-tuning a pre-trained language model is a typical way to apply pre-trained representations to downstream tasks. Since GBERT is a pre-trained Transformer encoder while the vanilla Transformer includes an encoder and a decoder, fine-tuning GBERT means that we replace the encoder in the vanilla Transformer with GBERT and train the new model in an end-to-end manner. Moreover, Liu and



**Fig. 2.** The architecture of GBERT-fused model, which fuses GBERT into the Transformer-based G2P model and is adapted from [16].

Lapata [17] found that using different learning rates for the pre-trained encoder and the randomly initialized decoder can lead to better convergence. We also leveraged this trick in our implementation.

## 2.3. Fusing GBERT into Transformer-based G2P Model

In addition to fine-tuning, another approach to integrate pre-trained language models is utilizing them as feature extractors, which may work better than the fine-tuning approach when the downstream tasks can not be easily represented by a Transformer encoder architecture [15]. One example is the BERT-fused model [16], which adopts a multi-head attention [20] and a drop net to adaptively control how each encoder and decoder layer of the vanilla Transformer model interacts with the output features of BERT. Since this method worked better than fine-tuning BERT and a naïve feature-based method in the medium-resource machine translation task, it is adapted in this paper to fuse GBERT into the Transformer-based G2P model, aiming to achieve better results in the medium-resource G2P scenario. An illustration is shown in Fig. 2, where GBERT replaces the BERT in the original BERT-fused model [16].

As shown in Fig. 2, the GBERT-fused model consists of  $L$  encoder layers and  $L$  decoder layers in addition to GBERT. For the  $l$ -th encoder layer, its input includes the output of the  $(l - 1)$ -th encoder layer (or the embeddings of the grapheme sequence when  $l = 1$ ) as well as the contextual grapheme representations provided by GBERT. For the  $l$ -th decoder layer, its input includes the hidden states of the  $(l - 1)$ -th decoder layer, the output of the last encoder layer and the contextual grapheme representations of GBERT. Specifically, in each encoder layer, an additional GBERT-Enc attention module is added to the original Transformer encoder layer in order to adaptively control how this layer interacts with the GBERT representations. In each decoder layer, there is a similar GBERT-Dec attention module for a similar purpose. Moreover, a drop net is used to regularize the network training, outputting one of the two inputs or their average results during training and outputting the average results during inference. More details can be found in the original paper of the BERT-fused model [16].

**Table 1.** The four languages used in our experiments.

Language	Language Family	Script Type	Word Example
Dutch	Germanic	Latin	afnemer
Serbo-Croatian	South Slavic	Latin	buđenje
Bulgarian	East Slavic	Cyrillic	абоната
Korean	Koreanic	Hangul	가치관

### 3. EXPERIMENTS

#### 3.1. Datasets

Experiments were conducted on the datasets of the SIGMORPHON 2021 G2P task [18]. The four most difficult languages (i.e., the languages with the highest word error rates) among all ten languages in the medium-resource subtask of the SIGMORPHON 2021 task was chosen, according to the G2P performance of the official baseline [21]. As listed in Table 1, they belong to different language families and have different script types. In the official settings, 8000, 1000 and 1000 pronunciation records were used for training, validation and test for each language. Following Elsaadany and Suter [22], Korean letters were decomposed into single-sound letters with hangul-jamo<sup>1</sup>, e.g., 가<sub>ㅏ</sub>감 → ㅏ ㅓ ㅓ ㅓ ㅓ.

A *medium-resource* G2P task and a *low-resource* G2P task were designed based on the datasets of these four languages. For the medium-resource task, the training, validation and test sets were the same as the official settings. For the low-resource task, we randomly sampled 1000 records from the original training set to form a smaller training set for each language, and used the original validation and test sets. Thus, the test set performance of these two tasks can be compared directly.

In addition, the word list for each language was collected from WikiPron [23] for GBERT pre-training. The words in the validation and test sets of the G2P tasks were excluded and the final word lists for these four languages in Table 1 contained 27.0k, 35.0k, 43.1k, and 14.1k words respectively. For each language, 90% of the words were used to train the monolingual GBERT and the remaining 10% were used for validation.

#### 3.2. Implementation

The GBERT for each language was a 6-layer Transformer encoder. Other hyperparameters of GBERT followed previous work [22]. The ratio of masked graphemes in a word was set as 20% for pre-training GBERT, which was higher than the ratio of masked words (15%) in BERT since we expected enough masked graphemes in short words. Our source code is released<sup>2</sup>. Evaluating the pre-trained GBERT models on the validation set of each language, the prediction accuracies of the masked graphemes were 53.48%, 58.43%, 80.66% and 40.63%, respectively. We can observe that they were all much higher than the accuracy of random prediction ( $\sim 2\%$ ), which shows the contextual relationship among graphemes in a word.

Finally, we compared five models as follows.

- **Imitation learning (IL)** [21] This baseline model adopted a neural transducer [24] that operated over explicit edit actions with imitation learning, and achieved similar performance to the Transformer model in the SIGMORPHON 2020 G2P task [10, 22]. We did not reimplement this model and just reported the single-model results in the paper of IL model [21] on our medium-resource G2P task.

- **Transformer** This baseline model adopted a Transformer-based architecture [20] and was implemented by us following previous work [22]. The model hyperparameters were tuned for different tasks of different languages, according to the performance on the validation set.
- **GBERT w/o fine-tuning** This model followed the proposed method in Section 2.2 except that the parameters of GBERT were frozen when tuning other model parameters.
- **GBERT fine-tuning** This model followed the proposed method in Section 2.2. Like previous work [17], different learning rates were used for the pre-trained GBERT encoder and the randomly initialized Transformer decoder during fine-tuning. Both learning rates were selected from 1e-3, 5e-4, 3e-4, 1e-4, 1e-5 based on the performance of the validation set for different tasks.
- **GBERT attention** This model followed the proposed method in Section 2.3 and had the same hyperparameters as the baseline Transformer model.

#### 3.3. Evaluation Metrics

Word error rate (WER) and phoneme error rate (PER) were used as the evaluation metrics in our experiments. WER is the percentage of words whose predicted phoneme sequences were not identical to the gold references. PER is the sum of the Levenshtein distance between the predicted and the reference phoneme sequences, divided by the sum of the reference lengths on the test set. The lower the WER and PER, the better the performance.

We conducted each experiment five times with different random seeds and reported the mean and standard deviation of the five results for each model. Note that the results of the IL model were quoted and 10 repetitions were used by its authors [21]. Thus, its standard deviations can not be compared with other models.

#### 3.4. Results

Table 2 shows the WER and PER results of different models on our medium-resource and low-resource G2P tasks. The Transformer baseline implemented by us outperformed the IL baseline on the medium-resource task of Dutch, but was not as good as IL on the other three languages. For the GBERT w/o fine-tuning model, its performance was much worse than the Transformer baseline in almost all experiments, especially for Korean. This indicates that the grapheme representations derived from the pre-trained GBERT can not provide all the necessary information for G2P conversion.

On the medium-resource G2P task, the GBERT fine-tuning model significantly outperformed its counterpart without fine-tuning for all four languages, and achieved lower WERs and PERs than the Transformer baseline for all languages except Korean. The GBERT attention model obtained the lowest WERs and PERs among all five models for all languages. All these results demonstrate the effectiveness of our proposed methods of fine-tuning GBERT or fusing GBERT into Transformer for the medium-resource G2P task. Although the GBERT attention model also adopted GBERT as a feature extractor, just like the GBERT w/o fine-tuning model, its advantage is that not only GBERT representations but also the original input of the Transformer-based G2P model is utilized by attention modules.

On the low-resource G2P task, the performance of all models decreased significantly compared to the medium-resource scenario,

<sup>1</sup><https://github.com/jonghwanhyeon/hangul-jamo>

<sup>2</sup><https://github.com/ldong1111/GraphemeBERT>

**Table 2.** The WER and PER results (%) of different models on our medium-resource and low-resource G2P tasks.

Model	Dutch		Serbo-Croatian		Bulgarian		Korean	
	WER	PER	WER	PER	WER	PER	WER	PER
<i>medium-resource</i>								
IL [21]	17.7 ± 1.3	-	38.9 ± 1.2	-	19.7 ± 1.7	-	18.9 ± 0.8	-
Transformer	16.86 ± 0.14	3.49 ± 0.05	39.50 ± 0.71	7.94 ± 0.14	20.72 ± 2.70	3.84 ± 0.74	19.26 ± 0.48	3.39 ± 0.10
GBERT w/o fine-tuning	19.98 ± 0.66	4.61 ± 0.48	43.92 ± 0.97	9.53 ± 0.75	23.24 ± 2.54	4.17 ± 0.40	23.06 ± 0.30	4.92 ± 0.15
GBERT fine-tuning	16.18 ± 0.23	3.59 ± 0.39	39.08 ± 1.05	7.83 ± 0.21	18.88 ± 2.31	<b>3.42 ± 0.33</b>	19.80 ± 0.62	3.52 ± 0.12
GBERT attention	<b>15.86 ± 0.21</b>	<b>3.38 ± 0.07</b>	<b>37.64 ± 0.71</b>	<b>7.67 ± 0.20</b>	<b>18.60 ± 1.92</b>	<b>3.42 ± 0.34</b>	<b>17.94 ± 0.71</b>	<b>3.16 ± 0.13</b>
<i>low-resource</i>								
Transformer	34.30 ± 0.66	9.39 ± 0.42	68.86 ± 1.08	15.41 ± 0.16	33.06 ± 1.90	6.07 ± 0.35	<b>29.72 ± 0.77</b>	<b>6.79 ± 0.35</b>
GBERT w/o fine-tuning	34.56 ± 0.72	9.13 ± 0.60	69.70 ± 0.69	15.88 ± 0.65	41.87 ± 0.89	9.15 ± 0.88	42.76 ± 1.04	12.66 ± 0.29
GBERT fine-tuning	<b>28.96 ± 0.69</b>	<b>6.94 ± 0.61</b>	<b>63.12 ± 0.76</b>	<b>13.29 ± 0.57</b>	<b>30.86 ± 1.66</b>	<b>5.30 ± 0.36</b>	32.78 ± 1.21	8.43 ± 0.11
GBERT attention	35.28 ± 0.66	9.41 ± 0.33	68.14 ± 0.68	15.06 ± 0.29	31.98 ± 1.32	5.76 ± 0.35	29.78 ± 0.60	6.81 ± 0.30

**Table 3.** The influence of the masked grapheme ratio for pre-training GBERT on the performance of the GBERT attention model for the medium-resource Dutch G2P task.

Mask Ratio (%)	Mask Accuracy (%)	WER (%)	PER (%)
15	53.01	16.34 ± 0.43	3.51 ± 0.08
20	53.48	15.86 ± 0.21	3.38 ± 0.07
30	51.32	15.88 ± 0.30	3.40 ± 0.08

indicating the importance of training data amount to the state-of-the-art neural G2P models. The GBERT fine-tuning model also outperformed the GBERT w/o fine-tuning model for all four languages and outperformed the Transformer baseline for all languages except Korean. However, the GBERT attention model performed better than the Transformer baseline only for Serbo-Croatian and Bulgarian, and performed not as good as the GBERT fine-tuning model for Dutch, Serbo-Croatian and Bulgarian. These results show that the method of fusing GBERT into Transformer may be more sensitive to the amount of training data than the method of fine-tuning GBERT because the former has a more complex model structure. The reason that our proposed method did not achieve satisfactory performance for Korean on the low-resource G2P task may be that the mask prediction accuracy of Korean was much lower than that of the other three languages as shown in Section 3.2, i.e., the contextual relationship among graphemes in Korean was weaker than that in the other three languages.

An additional experiment was conducted to investigate the influence of the masked grapheme ratio for pre-training GBERT on the performance of our proposed methods. The GBERT attention model for the medium-resource Dutch G2P task was taken as an example, and the results are shown in Table 3. We can observe that the higher mask ratios (20% and 30%) achieved lower WER and PER than the original ratio of 15% in BERT. One possible reason is that the average number of graphemes in a word is much smaller than the average number of words in a sentence and the grapheme space is much more compact than the word space. Thus, low mask ratios may constrain the model from discovering the contextual relationship among graphemes.

### 3.5. GBERT-based Transfer Learning For G2P Conversion

We also conducted an experiment to explore GBERT-based transfer learning, where the G2P data of another high-resource language was used to improve the performance of the low-resource G2P task. In this experiment, Dutch was selected as the low-resource language and English was chosen as the high-resource language since they belong to the same Germanic language family and have the same

**Table 4.** The WER and PER results (%) of different models by transfer learning with high-resource English G2P data on the low-resource Dutch G2P task.

Model	WER	PER
Transformer	24.54 ± 0.53	5.09 ± 0.22
GBERT w/o fine-tuning	33.30 ± 0.89	7.89 ± 0.25
GBERT fine-tuning	23.42 ± 0.82	4.84 ± 0.16
GBERT attention	<b>23.36 ± 0.82</b>	<b>4.76 ± 0.25</b>

Latin script type. The supervised training data of English contained 33,344 word-pronunciation pairs from the high-resource subtask of the SIGMORPHON 2021 task.

First, a bilingual GBERT was pre-trained by mixing 49.1k English words from WikiPron and the Dutch word list mentioned in Section 3.1. Following a variant of BERT [25], we added a language embedding to the input tokens of GBERT to distinguish different languages. Then, neural G2P models were built using the supervised training data of both English and Dutch. Following previous work [22], the words prefixed with a language tag were used as model inputs. The results of different models are shown in Table 4.

Comparing Table 4 with the low-resource results in Table 2, we can see that the WERs and PERs of all systems degraded significantly after transfer learning. Different from the low-resource results in Table 2, the GBERT attention model achieved the lowest WER and PER among all four models. This indicates that the GBERT attention model can benefit from the increased training data from similar high-resource languages, and our proposed GBERT-based methods can also be combined with the transfer learning strategy to obtain better performance.

## 4. CONCLUSION

In this paper, we have proposed a pre-trained grapheme model GBERT that outputs contextual grapheme representations. The training of GBERT requires only easily accessible word lists. In addition, two methods, namely fine-tuning GBERT and fusing GBERT into Transformer, have been developed to enhance the state-of-the-art Transformer-based G2P model with GBERT. Experiments on the Dutch, Serbo-Croatian, Bulgarian and Korean datasets of the SIGMORPHON 2021 G2P task show that the method of fusing GBERT can reduce the WER and PER of all languages on the medium-resource G2P task, while the method of fine-tuning GBERT can improve the G2P performance of most languages on the low-resource G2P task. In the future, we intend to improve the pre-trained grapheme model by developing new architectures and loss functions, and utilizing phrase-level or sentence-level training data.

## 5. REFERENCES

- [1] Isaac Elias, Heiga Zen, Jonathan Shen, Yu Zhang, Ye Jia, Ron J Weiss, and Yonghui Wu, “Parallel tacotron: Non-autoregressive and controllable TTS,” in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 5709–5713.
- [2] Changfeng Gao, Gaofeng Cheng, Runyan Yang, Han Zhu, Pengyuan Zhang, and Yonghong Yan, “Pre-training transformer decoder for end-to-end ASR model with unpaired text data,” in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 6543–6547.
- [3] Ryo Masumura, Naoki Makishima, Mana Ithori, Akihiko Takashima, Tomohiro Tanaka, and Shota Orihashi, “Phoneme-to-Grapheme Conversion Based Large-Scale Pre-Training for End-to-End Automatic Speech Recognition,” in *Proc. Interspeech 2020*, 2020, pp. 2822–2826.
- [4] Lucian Galescu and James F Allen, “Pronunciation of proper names with a joint n-gram model for bi-directional grapheme-to-phoneme conversion,” in *Seventh International Conference on Spoken Language Processing*, 2002.
- [5] Maximilian Bisani and Hermann Ney, “Joint-sequence models for grapheme-to-phoneme conversion,” *Speech communication*, vol. 50, no. 5, pp. 434–451, 2008.
- [6] Josef R Novak, Nobuaki Minematsu, and Keikichi Hirose, “WFST-based grapheme-to-phoneme conversion: Open source tools for alignment, model-building and decoding,” in *Proceedings of the 10th International Workshop on Finite State Methods and Natural Language Processing*, 2012, pp. 45–49.
- [7] Shubham Toshniwal and Karen Livescu, “Jointly learning to align and convert graphemes to phonemes with neural attention models,” in *2016 IEEE Spoken Language Technology Workshop (SLT)*. IEEE, 2016, pp. 76–82.
- [8] Sevinj Yolchuyeva, Géza Németh, and Bálint Gyires-Tóth, “Transformer based grapheme-to-phoneme conversion,” *Proc. Interspeech 2019*, pp. 2095–2099, 2019.
- [9] Kyle Gorman, Lucas FE Ashby, Aaron Goyzueta, Arya D McCarthy, Shijie Wu, and Daniel You, “The SIGMORPHON 2020 shared task on multilingual grapheme-to-phoneme conversion,” in *Proceedings of the 17th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology*, 2020, pp. 40–50.
- [10] Peter Makarov and Simon Clematide, “CLUZH at SIGMORPHON 2020 shared task on multilingual grapheme-to-phoneme conversion,” Association for Computational Linguistics, 2020.
- [11] Aliya Deri and Kevin Knight, “Grapheme-to-phoneme models for (almost) any language,” in *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2016, pp. 399–408.
- [12] Ben Peters, Jon Dehdari, and Josef van Genabith, “Massively multilingual neural grapheme-to-phoneme conversion,” in *Proceedings of the First Workshop on Building Linguistically Generalizable NLP Systems*, 2017, pp. 19–26.
- [13] Eric Engelhart, Mahsa Elyasi, and Gaurav Bharaj, “Grapheme-to-phoneme transformer model for transfer learning dialects,” *arXiv preprint arXiv:2104.04091*, 2021.
- [14] James Route, Steven Hillis, Isak Czeresnia Etinger, Han Zhang, and Alan W Black, “Multimodal, multilingual grapheme-to-phoneme conversion for low-resource languages,” in *Proceedings of the 2nd Workshop on Deep Learning Approaches for Low-Resource NLP (DeepLo 2019)*, 2019, pp. 192–201.
- [15] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 2019, pp. 4171–4186.
- [16] Jinhua Zhu, Yingce Xia, Lijun Wu, Di He, Tao Qin, Wengang Zhou, Houqiang Li, and Tieyan Liu, “Incorporating BERT into neural machine translation,” in *International Conference on Learning Representations*, 2019.
- [17] Yang Liu and Mirella Lapata, “Text summarization with pretrained encoders,” in *EMNLP-IJCNLP*, 2019, pp. 3730–3740.
- [18] Lucas FE Ashby, Travis M Bartley, Simon Clematide, Luca Del Signore, Cameron Gibson, Kyle Gorman, Yeonju Lee-Sikka, Peter Makarov, Aidan Malanoski, Sean Miller, et al., “Results of the second sigmorphon shared task on multilingual grapheme-to-phoneme conversion,” in *Proceedings of the 18th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology*, 2021, pp. 115–125.
- [19] Markéta Řezáčková, D Tihelka, and J Švec, “T5g2p: Using text-to-text transfer transformer for grapheme-to-phoneme conversion,” *Proc. Interspeech 2021*, pp. 6–10, 2021.
- [20] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin, “Attention is all you need,” in *Advances in neural information processing systems*, 2017, pp. 5998–6008.
- [21] Simon Clematide and Peter Makarov, “Cluzh at sigmorphon 2021 shared task on multilingual grapheme-to-phoneme conversion: variations on a baseline,” in *Proceedings of the 18th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology*, 2021, pp. 148–153.
- [22] Omnia ElSaadany and Benjamin Suter, “Grapheme-to-phoneme conversion with a multilingual transformer model,” in *Proceedings of the 17th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology*, 2020, pp. 85–89.
- [23] Jackson L Lee, Lucas FE Ashby, M Elizabeth Garza, Yeonju Lee-Sikka, Sean Miller, Alan Wong, Arya D McCarthy, and Kyle Gorman, “Massively multilingual pronunciation modeling with wikipron,” in *Proceedings of the 12th language resources and evaluation conference*, 2020, pp. 4223–4228.
- [24] Roei Aharoni and Yoav Goldberg, “Morphological inflection generation with hard monotonic attention,” in *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2017, pp. 2004–2015.
- [25] Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu, “MASS: Masked sequence to sequence pre-training for language generation,” in *International Conference on Machine Learning*. PMLR, 2019, pp. 5926–5936.