Comparing Writing Systems with Multilingual Grapheme-to-Phoneme and Phoneme-to-Grapheme Conversion

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Abstract

1 Introduction

The orthographic depth of an alphabetic orthography indicates the degree to which a written language deviates from simple one-to-one grapheme (letter) to phoneme (sound) correspondence.

Shallow (transparent) orthographies, also called phonemic orthographies, have a one-to-one relationship between its graphemes and phonemes, and the writing and reading of letters is very consistent. Spanish and Basque are examples of transparent orthographies.

In contrast, in deep (opaque) orthographies, the relationship is less direct, and the writer or reader must learn the arbitrarily irregular words. English and French are considered to have opaque orthographies.

Sequence-to-sequence models are very good at picking up on consistent patterns. Therefore, a seq2seq system should learn the regular writing systems much better than the irregular ones. That means that the performance of seq2seq models could be used as a measure of regularity of a writing system. The grapheme-to-phoneme (G2P) direction would suggest the difficulty of reading a language. Similarly, in the phoneme-to-grapheme (P2G) direction we would be looking at the inconsistencies of writing a language.

We use the transformer proposed in Wu et al. (2021) to compare the orthographies of 10 languages: Armenian (Eastern), Bulgarian, Dutch, French, Georgian, Serbo-Croatian (Latin), Hungarian, Japanese (Hiragana), Korean and Vietnamese (Hanoi). We use same data of the medium-resource languages from the SIGMORPHON 2021 G2P task (Ashby et al., 2021). We train a different model for each task and language, so there are 20 models in total.

The goal is not to build a perfect G2P and P2G system. Instead the goal is to build a translator which can indicate a degree of phonemic transparency and thus make it possible to rank orthographies. We do not have to translate a sequence of words into another sequence of words. Our model only requires translating a single word. Therefore, We can consider G2P and P2G as two translation tasks and apply the transformer at character level.

2 Related works

Sequence-to-sequence (seq2seq) models have been proven to be very successful on language translation tasks. Recently, attention (Bahdanau et al., 2016), transformers (Vaswani et al., 2017) and generative pre-training (GPT) (Radford and Narasimhan, 2018) have improved the performance of seq2seq models. Applying the transformer to character-level transduction tasks such as G2P has been proved to be a good option (Wu et al., 2021). It was one of the baselines in the SIGMORPHON 2020 G2P task (Gorman et al., 2020).

Many studies have discussed the transparency of orthographies based on the ease of reading and writing when learning a new language (Borleffs et al., 2017). However, there is not much work in NLP about measuring the level of transparency of an orthography. In an old work, three data-based algorithms were tested on three orthographies: Dutch, English and French (van den Bosch et al., 1994).

In a recent work, a minimalist GPT implementation has been used to compare 17 orthographies (Marjou, 2021) on the same G2P and P2G tasks. A unique multi-orthography model was trained to learn the writing and reading tasks on all languages at the same time. In other words, a single dataset containing samples of all studied orthographies was used.

On the one hand, the results show that Chinese, French, English and Russian are the most opaque regarding writing. English and Dutch are the most opaque regarding reading.

On the other hand, they indicate that Esperanto, Arabic, Finnish, Korean, Serbo-Croatian and Turkish are very shallow both to read and to write. Italian, Breton, German, Portuguese and Spanish are shallow to read and to write.

3 Material and methods

In order to compare the transparency of languages, multiple steps were needed: collecting data, preprocessing, training and evaluation. The Fairseq toolkit was used for these steps (Ott et al., 2019). All the code and data is available on GitHub[1].

3.1 Data

The SIGMORPHON 2021 G2P medium-resource data is used. It consists of 10,000 words for each of the previously mentioned 10 languages. Words containing less than two Unicode characters or less than two phone segments are excluded, as well as words with multiple pronunciations. The data is randomly split into training (80%), development (10%), and testing (10%) data.

This data was extracted from the English-language portion of Wiktionary[2] using WikiPron[3] (Lee et al., 2020). All data files contain UTF-8-encoded tab-separated values files. Each example occupies a single line and consists of a grapheme Unicode sequence, a tab character, and the corresponding phone IPA sequence, tokenized using the segments[4] library (Moran and Cysouw, 2018).

Reusing the SIGMORPHON data has many advantages. On the one hand, we can compare the results we obtain with the baseline and submissions. On the other hand, it assures that the data we are using is of good quality. In fact, some quality assurance actions have already been applied to the data, to reduce inconsistencies on the initial data. There could still be minor errors, but hopefully the impact of those will be very small. This way, the comparison between languages will be as fair as possible.

[1] https://github.com/juletx/writing-systems

[2] https://en.wiktionary.org

[3] https://github.com/kylebgorman/wikipron

[4] https://github.com/cldf/segments

3.2 Preprocessing

The data have to be preprocessed with fairseq so that it could be used for training. Phonemes are already separated with spaces but graphemes have to be separated on character level. Six files are needed for each language: two train, two dev, two test, each distinguished by the prefix of each language. One file is the source and one is the target, distinguished by grapheme or phoneme suffixes.

A minimum of 5 occurrences is set for each character, and the remaining ones are mapped to unknown. Table 1 shows the unique and average grapheme and phoneme counts for each language. We can see that there is some variability between languages. Some languages have similar unique grapheme and phoneme counts, while others are unbalanced. Unbalanced languages can't have a one-to-one correspondence between graphemes and phonemes. Even if these counts alone don't explain the results, they give us an idea of the complexity of the language.

For example, on the one hand, Georgian has the same amount of unique and average graphemes and phonemes. The frequency distribution of graphemes and phonemes in Georgian is the same, as it can be seen in Figures 1 and 2. On the other hand, Korean is a crear outlier if we look at grapheme counts. There are many unique graphemes, but the mean grapheme count of each words is very low. This means that each grapheme is matched to multiple phonemes.

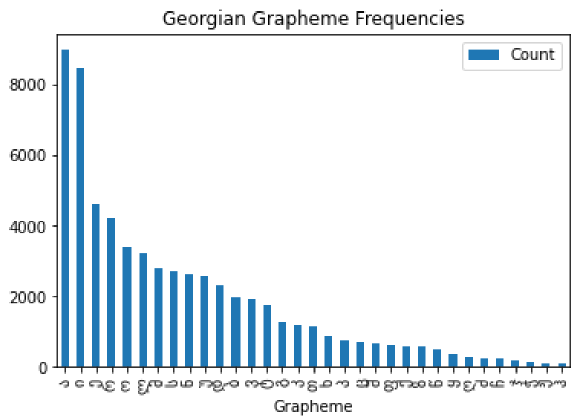

Figure 1: Frequency distribution of Georgian graphemes.

3.3 Training

We used fairseq to define the parameters of the model and train it. The parameters of the trans-

Language	Code	Graphemes	Phonemes	Mean Gra	Mean Pho
Armenian (Eastern)	arm_e	38	41	7.09	7
Bulgarian	bul	29	45	8.44	8.64
Dutch	dut	30	45	7.71	6.99
French	fre	37	37	7.52	5.75
Georgian	geo	33	33	7.74	7.74
Serbo-Croatian (Latin)	hbs_latn	27	61	7.47	7.36
Hungarian	hun	34	61	7.65	7.18
Japanese (Hiragana)	jpn_hira	76	64	4.21	6.56
Korean	kor	559	60	2.58	6.54
Vietnamese (Hanoi)	vie_hanoi	89	49	5.81	7.51
Average	average	95.2	49.6	6.62	7.13

Table 1: Unique and average grapheme and phoneme counts for each language

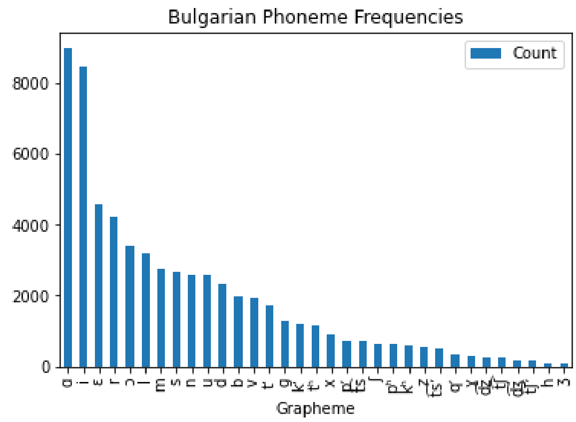

Figure 2: Frequency distribution of Georgian phonemes.

former are the ones defined in Wu et al. (2021) with a few changes. This transformer is smaller than usual because our character-level dataset is small. It has 4 encoder-decoder layers and 4 self-attention heads. The embedding size is 256 and the hidden size of the feed-forward layer is 1024. The resulting models have around 7.4M parameters.

ReLU was used as an activation function for the feed-forward layers. We use Adam optimizer with a learning rate of 0.001 and an inverse square root learning rate scheduler. We used a batch size of 400 and a the droput rate is set to 0.1. Label smoothing of 0.1 is also applied. Early stopping with a patience of 20 epochs was used to reduce training time and avoid overfiting. Only best and last model checkpoints are saved.

The training was done using the free GPUs offered by Google Colab. Each task was trained on a separate day with different GPUs. On the one hand, a Tesla K80 GPU was used for the G2P task, resulting in training times of around 10 minutes for each model. On the other hand, the P2G models were trained using a Tesla T4 GPU, reducing training times to around 5 minutes. The training process was monitored using TensorBoard and can be consulted in TensorBoard.dev[5]. Learning curves of all the models can also be seen in Figures 3 and 4

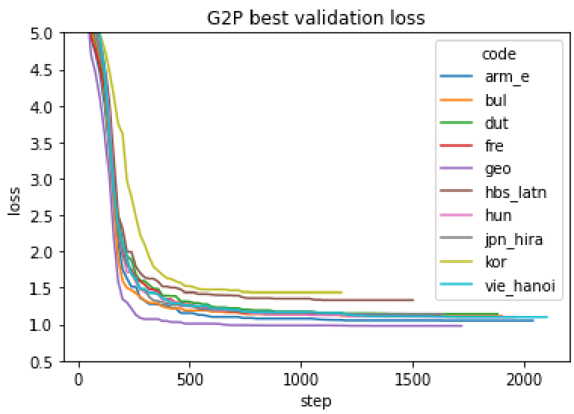

Figure 3: G2P validation loss learning curve.

3.4 Evaluation

Fairseq is used to make predictions using the checkpoint of the best models. Beam search with a beam size of 5 is used to make predictions. Predictions are generated and saved for each of the subsets. Based on those predictions, train, dev and test scores are computed for each language. Average scores are also computed for each task and subset.

The metric used to rank systems is word error

[5]https://tensorboard.dev/experiment/mcrHkdndR0ySobcxV1UxVA

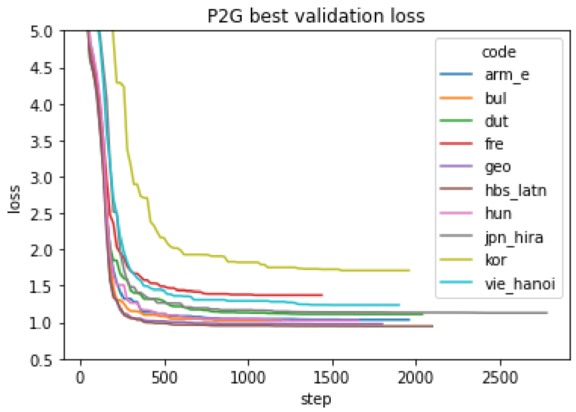

Figure 4: P2G validation loss learning curve.

rate (WER), the percentage of words for which the predicted sequence does not match the gold sequence. The average WER was also calculated for each task. This is the same metric that was used in SIGMORPHON 2021 Task 1.

4 Results

4.1 Comparison with baseline

The baseline for the SIGMORPHON 2021 G2P task is a neural transducer system using an imitation learning paradigm (Makarov and Clematide, 2018). Alignments are computed using ten iterations of expectation maximization, and the imitation learning policy is trained for up to sixty epochs (with a patience of twelve) using the Adadelta optimizer. A beam of size of four is used for prediction. Final predictions are produced by a majority-vote ten-component ensemble.

The G2P results are compared with the baseline results on the dev and test sets in Table 2 and Figure 5. The results are worse in all languages but the ranking between languages is maintained. As we said before, our aim is not to get perfect results, so our model is good enough for our aim.

4.2 Comparison between languages

Results for each task, language and subset are shown in Table 3. The results for each task can be seen in Figures 6 and 7.

As expected, training set results are much better than development and test set results, which are similar. Most of the times the training WER is close to 0, but there are some cases where the model doesn't even get good results in the training set.

If we only look at test results, we can plot the G2P and P2G scores of each language together in

Code	B Dev	T Dev	B Test	T Test
arm_e	4.50	6.5	7.00	8.90
bul	8.30	14.9	18.30	20.10
dut	10.80	12.0	14.70	16.90
fre	7.40	9.5	8.50	10.20
geo	0.00	0.3	0.00	0.10
hbs_latn	34.70	49.2	32.10	47.70
hun	1.50	2.8	1.80	1.90
jpn_hira	6.20	8.4	5.20	8.50
kor	18.40	33.4	16.30	30.20
vie_hanoi	1.30	4.0	2.50	6.00
average	9.31	14.1	10.64	15.05

Table 2: Comparison of the G2P WER results of our transformer with the baseline.

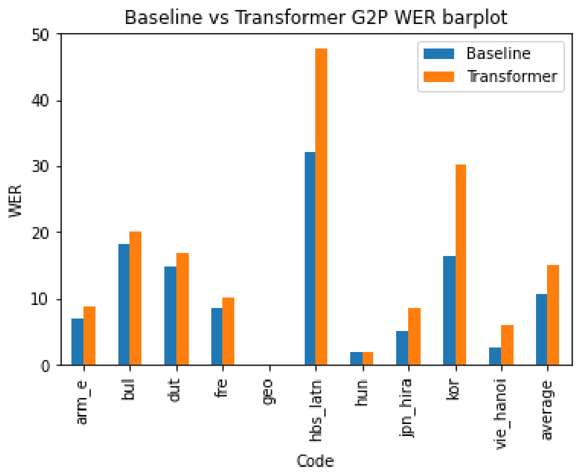

Figure 5: Comparison of the G2P WER results of our transformer with the baseline.

Figure 8. This way, we can compare and languages based on reading and writing tasks. If we plot them in a scatter plot, we can see how close languages are between them in Figure 9. We can use this to group languages that are similar.

First, Georgian gets almost perfect results both in reading and writing, which confirms that it has a very transparent orthography. Hungarian gets the second best results.

Japanese (Hiragana) and Armenian (Eastern) have similar scores, with a reading score of around 5% and a writing score that is close to 10%.

Next is Vietnamese (Hanoi) which has a much better score on writing (6.00) than on writing (16.30).

Dutch and Bulgarian have reading score of around 20 and writing scores of more or less 25.

Code	G2P Train	G2P Dev	G2P Test	P2G Train	P2G Dev	P2G Test
arm_e	1.16	6.5	8.90	0.57	4.40	5.70
bul	0.34	14.9	20.10	16.25	19.70	27.30
dut	2.59	12.0	16.90	2.67	18.00	23.00
fre	2.04	9.5	10.20	32.96	53.50	54.00
geo	0.06	0.3	0.10	0.12	0.30	0.50
hbs_latn	22.56	49.2	47.70	0.09	0.20	0.60
hun	0.64	2.8	1.90	0.84	6.20	4.80
jpn_hira	2.74	8.4	8.50	0.59	2.40	3.90
kor	19.27	33.4	30.20	11.84	22.80	22.10
vie_hanoi	0.44	4.0	6.00	5.35	15.00	16.30
average	5.18	14.1	15.05	7.13	14.25	15.82

Table 3: Results for each task, language and subset.

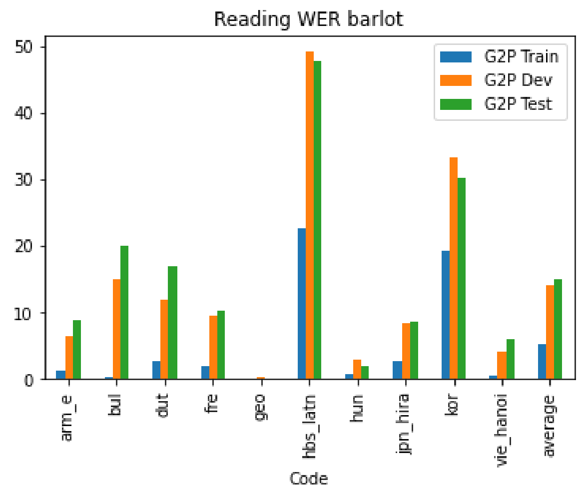

Figure 6: G2P results for each language and set.

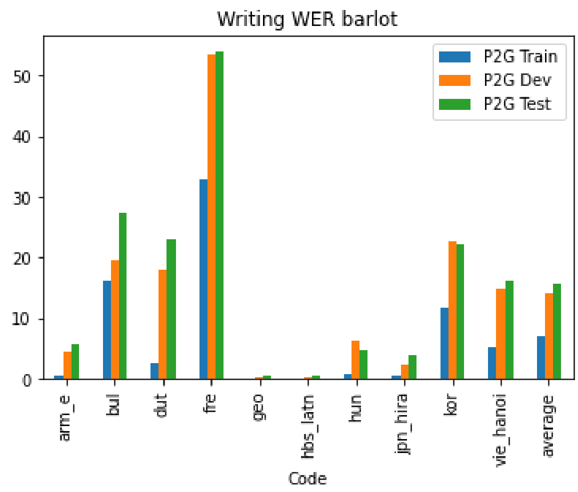

Figure 7: P2G results for each language and set.

Korean gets bad results both in reading (30.20) and on writing (22.10). ´ Finally, we can see that Serbo-Croatian and French are outliers. On the one hand, Serbo-Croatian gets very good score in writing (0.60) and very bad (47.7) in reading. On the other hand, French reading score is very bad (54.00), but writing score is better than average (10.20).

5 Conclusion

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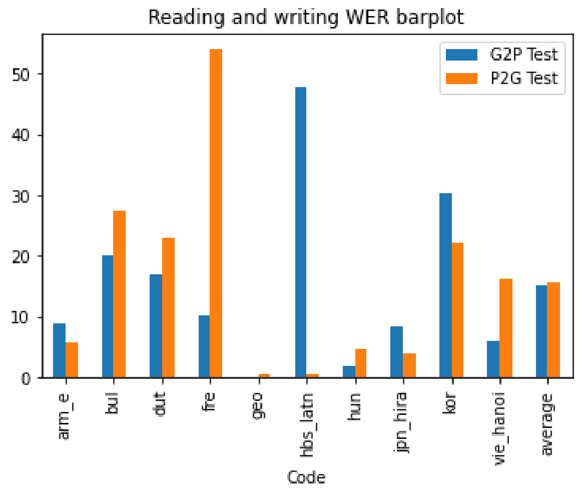

Figure 8: G2P and P2G barplot.

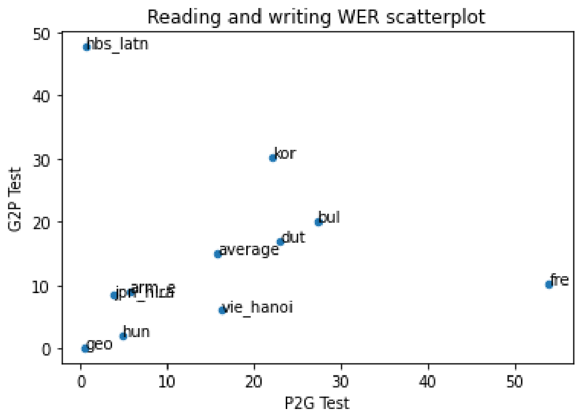

Figure 9: G2P and P2G scatterplot.

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