Abstract

Transliteration is a task of translating named entities from a language to another, based on phonetic similarity. The task has embraced deep learning approaches in recent years, yet, most ignore the phonetic features of the involved languages. In this work, we incorporate phonetic information into neural networks in two ways: we synthesize extra data using forward and back-translation but in a phonetic manner; and we pre-train models on a phonetic task before learning transliteration. Our experiments include three language pairs and six directions, namely English to and from Chinese, Hebrew and Thai. Results indicate that our proposed approach brings benefits to the model and achieves better or similar performance when compared to state of the art.

1 Introduction

Transliteration is a task that maps words from one language to another language guided by the pronunciation in both source and target language (Deselaers et al., 2009). Transliteration plays a significant role in machine translation (Hermjakob et al., 2008), it enables proper nouns such as names or places to be translated properly following the cross-linguistic conventions (He and Cohen, 2020). However, transliteration is not an easy task, many languages do not share alphabets and sound systems (?), such as Chinese and English. Moreover, in some languages like Chinese and Japanese, the characters do not contain any phonetic information (Xing et al., 2004), this makes the transliteration becomes harder.

In recent years, sequence-to-sequence (Seq2Seq) deep learning model shows advantages in transliteration task. Many work address transliteration using Seq2Seq architecture, based on attention mechanism and RNN family (Ameur et al., 2017; Kundu et al., 2018; Rosca and Breuel, 2016). These approaches directly train models end-to-end, neglecting the phonetic information. However, in some traditional statistical machine translation systems, introducing phonetic information into transliteration models has been proven helpful (Oh et al., 2009; Jiang et al., 2009; Kwong, 2009). A straightforward approach to use phonetic information is to build a cascade model (shown in Figure 1.a). It first converts the source word to phoneme sequence of the target language, and then converts the phonemes to target graphemes (Jiang et al., 2009). However, this approach suffers from the phoneme-to-grapheme conversion error (Oh et al., 2009) and the accumulated error in the cascade processing (Song and Kit, 2010). Recent research on multi-task learning (shown in Figure 1) achieves similar performance as the state-of-the-art in Chinese-to-English transliteration (He and Cohen, 2020). It defines a phonetic auxiliary task to help introduce phonetic information into Chinese-to-English transliteration. However, this model is distracted since one shared encoder needs to handle two tasks encoding. Besides, the phonetic features are not explicitly involved in the English-to-Chinese decoding process. But intuitively, using the phonetic feature directly to decode will be helpful.

In this paper, we propose a novel approach to introduce phonetic information into English-to-Chinese transliteration (shown in Figure 1.c). We are going to use both the source grapheme information and the phonetic information to do transliteration and explore whether it can bring improvements in performance. We firstly define an auxiliary pre-train task to convert English to Pinyin by using the vanilla Seq2Seq (Bahdanau et al., 2015). Where Pinyin is the official Chinese Mandarin phonetic writing system, which uses Latin alphabets and four diacritics to represents pronunciation (He and Cohen, 2020). The pre-trained encoder is a bridge between English and Chinese phoneme,
which contains the phonetic information of Chinese. Then, we train a dual-encoder Seq2Seq architecture to transliterate English to Chinese end-to-end. The left encoder is a randomly initialized and is responsible for capturing English features. The right encoder is pre-trained previously, introducing phonetic information into the end-to-end transliteration.

Our experiment is based on two datasets, one is NEWS 2018\(^1\) English-to-Chinese name entity transliteration dataset (Chen et al., 2018), another is the DICT dataset\(^2\) released by (He and Cohen, 2020). We choose the widely-used word accuracy (ACC) (Grundkiewicz and Heafield, 2018; He and Cohen, 2020) and accuracy with alternating character table\(^3\) (ACC-ACT) (He and Cohen, 2020) for evaluation. We report both ACC and ACC-ACT of baseline and our approach in two datasets. More details can be found in section 4. We also compare our model with other systems, and demonstrate the effectiveness of our idea.

2 Related Work

Phonetic information is regarded as highly-related feature in the machine transliteration task. They are commonly being used in the model to bring positive effect(?). For example, in Chinese-related transliteration task, pinyin as a kind of phonetic information of Chinese could be involved (Oh et al., 2009). For a simple way, we can map a phrase to its pronunciation in the source language and convert these pronunciations to the target words (?), which is a cascade process. In this occasion, errors will be propagated forward following the stream, so we design the model to avoid this type of problem. A previous work reveals that introducing Pinyin into the model will be useful for a multi-task model (He and Cohen, 2020), but multi-task learning cannot focus on each task concentratedly at the same time. So we utilize it in another way to explore its influence.

For many NLP’s applications like Neural Machine Translation (Neubig, 2017), Seq2Seq is general and effective way to transfer a specific sequence to another (Rosca and Breuel, 2016). Here, we firstly propose a novel design of dual-encoder which is able to melting different information (Hosu et al., 2018), and we use vanilla Seq2Seq model dealing with the mapping between English and Pinyin (Jiang et al., 2009).

3 Model

3.1 Process of Transliteration

Consider the process of a native Chinese speaker doing English-to-Chinese transliteration. First, he/she will read out the English word and guess its possible pronunciation in Chinese. Then, he/she will search the Chinese characters that have similar pronunciation from his/her mind. Finally, he/she will determine the Chinese characters based on his knowledge of English and Chinese. We model this process as following:

$$ P(T|S, \hat{Ph}) = \prod_{j=1}^{J} P(t_j|T_{<j}, S, \hat{Ph}) $$ (1)

\(^1\)Available at: [http://workshop.colips.org/news2018/](http://workshop.colips.org/news2018/).
\(^2\)Available at: [https://github.com/Lawhy/Multi-task-NMTransliteration/](https://github.com/Lawhy/Multi-task-NMTransliteration/).
\(^3\)The table we used is available at: [https://github.com/Lawhy/Multi-task-NMTransliteration/tree/master/mnmt/alternating_character_table](https://github.com/Lawhy/Multi-task-NMTransliteration/tree/master/mnmt/alternating_character_table).
3.2 Two-step Modeling

We design a two-step solution to model the whole process. In the first step, we model the $P\hat{h}$. We define an auxiliary task to map English to Chinese Pinyin. As shown in Figure 2.a, we use a Seq2Seq model to map English to Chinese Pinyin. Here gated recurrent units (GRU) (Chung et al., 2014) are applied in encoder and decoder. The encoder uses Bidirectional GRU while decoder uses standard GRU. The embedding layers are randomly initialised. The attention mechanism we used is proposed in (Bahdanau et al., 2015). Dropout is exploited between Embedding layers and GRU layers in both encoder and decoder (Srivastava et al., 2014). The context vector $c_i$ is computed as the weighted sum of $h_j$:

$$c_i = \sum_{j=1}^{T_x} a_{ij} h_j$$  \hspace{1cm} (3)

The weight $a_{ij}$ is the attention score, computed by softmax function:

$$a_{ij} = \frac{\exp(score(s_{i-1}, h_j))}{\sum_{k=1}^{T_x} \exp(score(s_{i-1}, h_k))}$$  \hspace{1cm} (4)

The score function is in the following form:

$$score = v^\top \tanh (U[s_{i-1}; h_j])$$  \hspace{1cm} (5)

Where $v$ and $U$ are the weight matrices that model need to learn.

Teacher forcing strategy (Bengio et al., 2015) is used during training to correct predictions to avoid error accumulating. After training, we take out the encoder and treat it as the mapping function $\phi$:

$$\phi(X) = enc_1(X)$$  \hspace{1cm} (6)

In the second step, we train a dual-encoder Seq2Seq architecture end-to-end (Shown in Figure 2.b). The left encoder is randomly initialised, which is to model the English letters. The right encoder is the encoder trained in the first step, which contains phonetic information. Both two encoders...
have the same structure. When an English letter sequence feeds into the model, it will be separately encoded by two encoders. The attention mechanism will calculate two context vectors \( c^{(1)}_i \) and \( c^{(2)}_i \). The calculation of context vectors follows Equation (3), Equation (4) and Equation (5). Note that \( v \) and \( U \) in Equation (5) are different for two context vector calculations. The two context vectors then will be weighted averaged by the following equations:

\[
c^{(avg)}_i = w^{(1)}_i c^{(1)}_i + w^{(2)}_i c^{(2)}_i
\]

\[
w_i = \text{softmax}(M[c^{(1)}_i; c^{(2)}_i])
\]

Where \( M \) is a matrix to convert \([c^{(1)}_i; c^{(2)}_i]\) to a two-dimensional vector. The two weights indicate the contribution of two context vectors and promise the dual-encoder Seq2Seq at least has a similar performance as the standard Seq2Seq. In the extreme situation, if the context vector with phonetic information is useless, the weight will be extremely closed to zero. We name this design as integration gate.

4 Experiments

Due to the limitations from the approaches of Cascade and MultiTask, we propose a new solution of introducing phonetic information into a dual-encoder Seq2Seq model and verify if it can bring better performance in the English-to-Chinese transliteration task. To prove the feasibility and effectiveness of our idea, we put forward the following two hypotheses based on our reasoning in Section 3.

1. Hypothesis 1: We hypothesize that a dual-encoder Seq2Seq model should at least keep the same or improve the performance of English-to-Chinese transliteration task as the single-encoder Seq2Seq model.

2. Hypothesis 2: We hypothesize that a dual-encoder Seq2Seq model introducing phonetic information should at least keep the same or improve the performance of English-to-Chinese transliteration task as the randomly initialized dual-encoder Seq2Seq model (baseline).

There is straightforward intuitiveness for hypothesis 1: in our architecture, we can promise that our model won’t be worse than the vanilla sequence-to-sequence model because of the integration gate. For hypothesis 2, the pre-trained block would like to produce a good start point for optimization, and these initialized parameters will be used to correct the result from the left side at the beginning.

Based on the two hypotheses, we start two sets of controlled experiments and aim to account for a conclusion of whether introducing phonetic information into a dual-encoder Seq2Seq model can bring better performance from our experimental result.

4.1 Baseline

On the purpose to compare with our model that is going to introduce phonetic information, we initialize the right part randomly as well. And in this way, we will know that the improved performance is for the introduced phonetic information instead of more parameters. So we choose this whole randomly initialized model as baseline.

4.2 Evaluation

Word accuracy (ACC) and accuracy with alternating character table (ACC-ACT) are used to measure the model performance in our experiments.

\[
ACC = \frac{1}{N} \sum \text{Criterion}(y, \hat{y})
\]

The \( \text{Criterion} \) we use here is a function which will be 1 if all characters in \( y \) and \( \hat{y} \) are matched. The drawback of ACC is that it will ignore the case that we will get more than one transliteration result, and in this way the performance of system will be underestimated. For example, there are some different results like ‘卢娜’ and ‘卢纳’, which is related to the gender of name, according to the same English word, and ACC will treat is as wrong result (He and Cohen, 2020).

\[
\text{ACC-ACT}
\]

Another novel evaluation ACC-ACT (He and Cohen, 2020) is used to improve the flaw of ACC. An alternative character table is applied to check if two different word should be treated as the same right answer. The following procedure shows how to calculate ACC-ACT, where MED is the minimum edit distance and subscript \( t \) indicates the position of the character. Where \( \text{Criterion}(y, \hat{y}) = 1 \) if \( \text{MED}(y, \hat{y}) = 0 \) (which covers all the cases for ACC) OR the meet the following conditions in order:
Comparison with Single-Encoder Seq2Seq

We compare our model with the single-encoder Seq2Seq to prove dual-encoder Seq2Seq can get at least similar performance as the single-encoder Seq2Seq. We report the best test accuracy of our model and single-encoder Seq2Seq with different numbers of layers in both DICT and NEWS with different numbers of layers in both DICT and NEWS test sets. We can observe in most cases our dual-encoder model gets improvement in accuracy. However, when the number of layers is set to 3, our model gets a relative lower accuracy (0.006 lower) than single-encoder Seq2Seq without drastic decrease.

Comparison with Baseline

We report the best performance of our models and baseline models with different numbers of layers (hidden size of each layer is set to 512) in both DICT test set and NEWS test-set, shown in Table 2. We can observe our model in most cases achieves better ACC and ACC-ACT than the randomly initialised baseline model. The best performance in both DICT and NEWS are achieved by our models, which are 0.732 (3-layers) and 0.740 (2-layers) respectively. However, in the condition that the number of layers is set to 3, our model gets the same performance in NEWS as the baseline. The overall results demonstrate that using the encoder weights pre-trained in the auxiliary English-to-Pinyin transliteration task can improve or at least keep the same performance as the randomly initialised dual-encoder Seq2Seq model.

Results in Auxiliary Task

Table 3 shows the test-set accuracy of the main task (English to Chinese) and pre-trained auxiliary task (English to Pinyin) of our model and baseline in different conditions. The overall results demonstrate that using the encoder weights pre-trained in the auxiliary English-to-Pinyin transliteration task can improve or at least keep the same performance as the randomly initialised dual-encoder Seq2Seq model.

| Layers | DICT | NEWS |
|--------|------|------|
| 1      | 0.714 | 0.726↑ | 0.709  | 0.716↑ |
| 2      | 0.721 | 0.729↑ | 0.724  | 0.740↑ |
| 3      | 0.723 | 0.732↑ | 0.729  | 0.723↓ |

Table 1: The accuracy of single-encoder Seq2Seq and our dual-encoder Seq2Seq with different numbers of layers in DICT and NEWS test-sets. The hidden size of both models are set to 512. The up-arrow means the increase of our model’s ACC comparison to single-encoder Seq2Seq, the down-arrow refers to the decrease.

4.4 Results and System Comparison

Hyper-parameter Setting

In our experiment, we used 1, 2 and 3 layers GRU with the dimension of 512 for both left part of dual-encoder and the decoder, and the pre-trained encoder is of the same size either in order to make comparison with He and Cohen (2020). Additionally, we use the dropout mitigating the problem of over-fitting with the probability of 0.02 for both pre-train model and end-to-end model in DICT. Also, we choose the probability of 0.02 and 0.2 for pre-train and end-to-end respectively in the dataset NEWS. We use the ReduceLROnPlateau scheduler to control learning rate. The initial learning rate is set to 0.001 and the reduction factor is set to 0.3. If the validation accuracy does not improve in the next 3 consequent epochs, the learning rate will reduce by multiplying the factor. We also apply early-stopping to monitor the validation accuracy, if it does not increase within 5 consequent epochs, the training process will be stopped. The maximum epoch is set to 50.

Training Strategy

We pre-train the model from English to Pinyin for using phonetic information to assist the transliteration. Then use the pre-trained encoder to initialize the right part of the dual-encoder and directly train the model end-to-end without freezing (Drexler and Glass, 2018). The training strategy are inspired by the following thoughts: a) if we use the trained encoder that is about English and Pinyin to initialize the right part, it indicates that we would like to have a good start point to train our model. b) Importantly, the phonetic information contained in the pre-trained encoder will guide the learning procedure of the randomly initialised encoder through back propagation.

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Pinyin). We can see the auxiliary task accuracy goes up with the increasing number of layers in both datasets. The main task accuracy is positively correlated to the auxiliary task accuracy overall, but there is an exception in the NEWS dataset. In the condition that the number of layers is set to 3, the auxiliary task accuracy is pretty high, but the main task accuracy is relatively low. We speculate this exception is related to over-fitting.

| Layers | ACC | ACC_ACT | ACC | ACC_ACT |
|--------|-----|---------|-----|---------|
| 1      | 0.715 | 0.737 | 0.726 (↑ 0.011) | 0.748 (↑ 0.011) |
| 2      | 0.724 | 0.745 | 0.729 (↑ 0.005) | 0.752 (↑ 0.007) |
| 3      | 0.726 | 0.749 | **0.732 (↑ 0.006)** | **0.754 (↑ 0.005)** |

Table 3: The accuracy of our model in both main task and auxiliary task in DICT and NEWS.

**Comparison with Other Systems** We compare our model with Multitask (He and Cohen, 2020) and BiDeep (Grundkiewicz and Heafield, 2018), and report the ACC and ACC-ACT in Table 4, where BiDeep is the state-of-the-art model. The performance of Multitask and BiDeep both come from He and Cohen’s paper. We report our 3-layers model and 2-layers model considering the fairness of comparison. Our 3-layers model has a similar parameter size (2 layer GRU with 512 hidden units) to He and Cohen’s Multitask model. The performance of Multitask and BiDeep both come from He and Cohen’s Multitask model. In DICT, our 2-layers dual-encoder Seq2Seq gets the same ACC (0.729) as Multitask model, and achieves a slightly higher ACC-ACT (0.001 higher) than Multitask model. Our 3-layer model presents the same ACC (0.732) as BiDeep in DICT, but gets slightly lower ACC-ACT (0.001 lower) than BiDeep. In NEWS, our 3-layers model achieves the highest ACC and the second-highest ACC-ACT. Results indicate our model is close to the state-of-the-art level.

**NEws 2018 Official Test** We use our 2-layers model trained on NEWS dataset to transliterates the NEWS 2018 official test set and submit the result to the evaluation website provided by the NEWS workshop organizer. Table 5 shows the leaderboard of NEWS 2018 English-to-Chinese transliteration task (accessed 31 March 2021), where user “romang” refers to Grundkiewicz and Heafield (2018), “Lawhy” refers to He and Cohen (2020).
eration task. Here the F-score refers to the mean F-score, which measures how different, on average, the top transliteration candidate is from its closest reference. The ACC here is slightly different, which measures the correctness of the first transliteration candidate in the candidate list produced by a transliteration system. Our ACC ranks second (the same as He and Cohen’s Multitask), and F-score ranks third in the leaderboard.

5 Analysis and Discusions

In the experiments, by validating two hypotheses we argue that using the dual-encoder Seq2Seq with the auxiliary pre-train encoder can efficiently introduce phonetic information to transliterate English to Chinese. First, we prove the performance of our dual-encoder Seq2Seq is at least at a similar level as the single-encoder Seq2Seq’s, and in most cases performs better, as shown in Table 1. Then, to exclude the influence of bigger parameter size and verify the phonetic information in the pre-trained encoder does work, we compare our model with the baseline that has the same architecture but randomly initialised. In almost all cases, our model with the pre-trained encoder performs better than the baseline. However, for the NEWS dataset, we observe when the number of layers is set to 3, the model performs not very well. We speculate the model is overfitting since our dropout probability is quite small and both baseline and our model shows a decrease in accuracy. The overall results demonstrate our approach does improve the transliteration performance.

Our model provides a new feasible path to introduce phonetic information, and it can be widely deployed across many different language pairs. For languages that characters do not contain any phonetic information, such as Japanese and Korean, transliterating another language word to their graphemic form is often harder than to their phonetic form (Kang and Kim, 2000; Ravi and Knight, 2009) (such as IPA), since the phonetic form is more fine-grained. In this context, our model can offer helps to use phonetic information to correct transliteration.

6 Conclusion and Future Work

We argue that using additional phonetic information during decoding is an effective way to improve the transliteration result. And our experiments show that our proposed dual-encoder model can successfully introduce phonetic features and achieve similar state-of-the-art performance. Our model provides a new feasible path to introduce phonetic information, and it can be widely deployed across many different language pairs. We think there may be some potential research to improve the performance. For example, some knowledge of the tone of Chinese can be accessed during introducing phonetic information to make the result more accurate and explainable.

References

Mohamed Seghir Hadj Ameur, Farid Meziane, and Ahmed Guessoum. 2017. Arabic machine transliteration using an attention-based encoder-decoder model. Procedia Computer Science, 117:287–297.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

Samy Bengio, Oriol Vinyals, Navdeep Jaitly, and Noam Shazeer. 2015. Scheduled sampling for sequence prediction with recurrent neural networks. In Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 1, NIPS’15, page 1171–1179, Cambridge, MA, USA. MIT Press.

Nancy Chen, Rafael E. Banchs, Xiangyu Duan, Min Zhang, and Haizhou Li, editors. 2018. Proceedings of the Seventh Named Entities Workshop. Association for Computational Linguistics, Melbourne, Australia.

Junyoung Chung, Caglar Gulcehre, Kyunghyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

Thomas Deselaers, Saša Hasan, Oliver Bender, and Hermann Ney. 2009. A deep learning approach to machine transliteration. In Proceedings of the Fourth Workshop on Statistical Machine Translation, pages 233–241.

Jennifer Drexler and James Glass. 2018. Combining end-to-end and adversarial training for low-resource speech recognition. In 2018 IEEE Spoken Language Technology Workshop (SLT), pages 361–368. IEEE.

Roman Grundkiewicz and Kenneth Hearfield. 2018. Neural machine translation techniques for named entity transliteration. In Proceedings of the Seventh Named Entities Workshop, pages 89–94, Melbourne,
Australia. Association for Computational Linguistics.

Yuan He and Shay B Cohen. 2020. English-to-chinese transliteration with phonetic auxiliary task. In Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing, pages 378–388.

Ulf Hermjakob, Kevin Knight, and Hal Daumé III. 2008. Name translation in statistical machine translation-learning when to transliterate. In Proceedings of ACL-08: HLT, pages 389–397. Citeseer.

Ionel Alexandru Hosu, Radu Cristian Alexandru Iacob, Florin Brad, Stefan Ruseti, and Traian Rebedea. 2018. Natural language interface for databases using a dual-encoder model. In Proceedings of the 27th International Conference on Computational Linguistics, pages 514–524.

Xue Jiang, Le Sun, and Dakun Zhang. 2009. A syllable-based name transliteration system. In Proceedings of the 2009 Named Entities Workshop: Shared Task on Transliteration (NEWS 2009), pages 96–99.

In-Ho Kang and Gil Chang Kim. 2000. English-to-korean transliteration using multiple unbounded overlapping phoneme chunks. In COLING 2000 Volume 1: The 18th International Conference on Computational Linguistics.

Soumyadeep Kundu, Sayantan Paul, and Santanu Pal. 2018. A deep learning based approach to transliteration. In Proceedings of the seventh named entities workshop, pages 79–83.

Olivia OY Kwong. 2009. Phonological context approximation and homophone treatment for news 2009 english-chinese transliteration shared task. In Proceedings of the 2009 Named Entities Workshop: Shared Task on Transliteration (NEWS 2009), pages 76–79.

Graham Neubig. 2017. Neural machine translation and sequence-to-sequence models: A tutorial. arXiv preprint arXiv:1703.01619.

Jong-Hoon Oh, Kiyotaka Uchimoto, and Kentaro Torisawa. 2009. Can chinese phonemes improve machine transliteration?: A comparative study of english-to-chinese translation models. In Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing, pages 658–667.

Sujith Ravi and Kevin Knight. 2009. Learning phoneme mappings for transliteration without parallel data. In Proceedings of human language technologies: The 2009 annual conference of the north american chapter of the association for computational linguistics, pages 37–45.

Mihaela Rosca and Thomas Breuel. 2016. Sequence-to-sequence neural network models for transliteration. arXiv preprint arXiv:1610.09565.

Yan Song and Chunyu Kit. 2010. Does joint decoding really outperform cascade processing in english-to-chinese transliteration generation? the role of syllabification. In 2010 International Conference on Machine Learning and Cybernetics, volume 6, pages 3323–3328.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: A simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(56):1929–1958.

Hongbing Xing, Hua Shu, and Ping Li. 2004. The acquisition of chinese characters: Corpus analyses and connectionist simulations. Journal of Cognitive Science, 5(1):1–49.