Multimodal neural pronunciation modeling for spoken languages with logographic origin

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Abstract

Graphemes of most languages encode pronunciation, though some are more explicit than others. Languages like Spanish have a straightforward mapping between its graphemes and phonemes, while this mapping is more convoluted for languages like English. Spoken languages such as Cantonese present even more challenges in pronunciation modeling: (1) they do not have a standard written form, (2) the closest graphemic origins are logographic Han characters, of which only a subset of these logographic characters implicitly encodes pronunciation. In this work, we propose a multimodal approach to predict the pronunciation of Cantonese logographic characters, using neural networks with a geometric representation of logographs and pronunciation of cognates in historically related languages. The proposed framework improves performance by 18.1% and 25.0% respective to unimodal and multimodal baselines.

1 Introduction

In phonographic languages, there is a direct correspondence between graphemes and phonemes (Defrancis, 1996), though this correspondence is not always one-to-one. For example, in English, the word table corresponds to the pronunciation [ˈteɪbl], in which each alphabetic character corresponds to one phoneme, and the character e is mapped to silence. However, in logographic languages, the correspondence between graphemes and phonemes is more ambiguous (Defrancis, 1996), as only some sub-units in a grapheme are indicative of its phonemes. Korean1, Vietnamese2 and Chinese languages (e.g. Cantonese) are examples of logographic languages, all belonging to the Han logographic family. Similar to pronunciation modeling in phonographic languages, in which words are broken down into characters and modeling is done at the character level, pronunciation modeling in logographic languages requires decomposing logographs into sub-units and extracting only sub-units carrying pronunciation hints. As the correspondence of Han logograph to phoneme is intricately complex with many sub-rules or exceptions (Hashimoto, 1978), it is challenging to computationally model these correspondences using white box approaches (e.g. graphical model). Instead, we exploit neural networks, as they (1) can flexibly model the implicit similarity of grapheme-phoneme relationships across languages with Han origin, (2) can automatically learn the most relevant knowledge representation with minimal feature engineering (LeCun et al., 2015), such as extracting pronunciation hints from logographic representations.

Due to historical contact, there is much lexical overlap across Han logographic languages, as they borrowed words from one another (Rokuro, 1969; Miyake, 1997; Loveday, 1996; Sohn, 2001; Alves, 1999). As a result, cognates in different languages are written using identical graphemes but pronounced differently. For example, [she] in Mandarin and [sip] in Cantonese are cognates; their pronunciations are different yet they are written using the same logograph (懾), which represents “admire”. Though Han logographic languages are mutually unintelligible (Tang and Van Heuven, 2009; Handel, 2015), the correspondence of Han logographic graphemes to phonemes across languages is often similar in systematic ways (Cai et al., 2011; Frellesvig and Whitman, 2008; Miyake, 1997). The shared characteristics in pronunciation of cognates could be leveraged in deciphering the pronunciation of Han logographs. In this work, we proposed a neural pronuncia-

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1A large portion of Korean vocabulary are Sino-Korean written in Hanja (Korean logographs) (Sohn, 2001)

2Traditional Vietnamese vocabulary comprises of Sino-Vietnamese words written by Chinese logographs and locally-invented Nom logographs (Alves, 1999).
tion model that exploits both embeddings of logosgraphs and cognates’ phonemes. The proposed model significantly improves pronunciation prediction of logosgraphs in Cantonese.

2 Related Work

The basic units in writing (graphemes) of Han logosgraphic languages are logosgraphs. A word contains one or more logosgraphs and a logosgraph consists of one or more radicals. The pronunciation of a logosgraph corresponds to a syllable which has three phonemes: onset, nucleus and coda.

Grapheme-to-phoneme (G2P) approaches such as (Xu et al., 2004; Chen et al., 2016) predicted a Han logosgraph’s pronunciation from its local context in a phrase. This was similar to predicting a Latin word’s pronunciation from its surrounding words, essentially treated individual logosgraphs as the basic units of the model and did not delve further into the logosgraphic sub-units (the radicals).

While we are unaware of any work that derives features for pronunciation prediction from logosgraphs, there are recent work in deriving representation of logosgraphs for various semantic tasks. Some methods (Shi et al., 2015; Ke and Hagiwara, 2017; Nguyen et al., 2017; Zhuang et al., 2017) decomposed logosgraphs into sub-units using expert-defined rules and then extracted the relevant semantic features. Other methods use convolutional neural network to extract features from the images of logosgraphs (Dai and Cai, 2017; Liu et al., 2017; Toyama et al., 2017). Other works combined multiple level of information for feature extraction, using both logosgraph and sub-units obtained from logosgraph decomposition (Dong et al., 2016; Han et al., 2017; Peng et al., 2017; Yu et al., 2017; Yin et al., 2016).

In this work, we explicitly looked at the relationship between a logosgraph’s constituent radicals and its pronunciation. Among Han logosgraphs, 81% of frequently used logosgraphs are semantic-phonetic compounds (Li and Kang, 1993) which consist of radicals that might contain phonetic or semantic hints (Hsiao and Shillcock, 2006). The pronunciation of a logosgraph could conceivably be predicted from the phonetic radicals. Furthermore, the relative position of radicals in the logosgraph might also offer clues about it pronunciation. Table 1 shows an example of such intricate relationships between a logosgraph’s pronunciation and its constituent radicals. All Han logosgraphs in the table have a common phonetic radical (in red), which offers an inkling of the pronunciation of these logosgraphs. For instance, logosgraphs that have the phonetic radical on the left (剖 and 部) share a similar pronunciation in Korean (in blue) while logosgraphs that have the phonetic radical on the right (陪, 賠, and 蓓) share a similar pronunciation in Mandarin, Cantonese and Vietnamese. Note that for each logosgraph, their pronunciations across the different languages share similarities: when the phonetic radical is on the left, the nucleus ends in a back vowel like u or o, whereas when the phonetic radical is on the right, the nucleus ends in a front vowel like i.

| Position of 部 | 部 | 部 | 部 |
|-------------|---|---|---|
| Mandarin    | pou | bu | pei | pei | bei |
| Cantonese   | fau | bou | pui | pui | bui |
| Korean      | pwu | pwu | pay | pay | pay |
| Vietnamese  | phau | bo | boi | boi | bui |

Table 1: The position of radicals affects pronunciations. All logosgraphs share a common radical in red. Similar pronunciations for 剖 and 部 are bolded in blue. Similar pronunciations for 剒, 賠, and 蓓 are bolded in green. The pronunciation of a logosgraph in Mandarin, Cantonese, Korean and Vietnamese are represented by Pinyin, Jyutping, Yale, and Vietnamese alphabet symbols respectively.

The example in Table 1 explains the motivation for our proposed approach to predict a logosgraph’s pronunciation by modelling both the constituent radicals and their geometric positions. Furthermore, the proposed approach can generalize to unseen logosgraphs if the co-occurrence patterns of their constituent radicals have been learnt.

3 Model

We first describe a geometric decomposition of logosgraphs and then different neural pronunciation models for logosgraphs. Finally, we present a multimodal neural model that incorporates both logosgraphic input and the cognates’ phonemes in predicting pronunciation of logosgraphs.

Representation of Han logosgraphs

The majority of logosgraphs (characters) in Han logosgraphic language family comprise of a radical that indicates its nominal semantic category and a phonetic radical that gives an inkling of the pronunciation (Defrancis, 1996). Thus, patterns of co-occurrence of radicals across logosgraphs might
be exploited to find the phonetic radicals, which in turn can suggest the corresponding pronunciation of a logograph. Using this intuition, we model the pronunciation of logographs at the radical level.

We investigated two representations of radicals in a logograph. In the first approach, a logograph is represented as a bag of its unordered constituent radicals (BoR), encoded as a vector of radical counts. The second approach is to use a decomposition of radicals in the logograph that retains the original geometric organization of the radicals. The geometric decomposition (GeoD) approach preserves important cues about the word’s pronunciation in the relative position of the radicals. For example, differentiating the left radical from the right radical in a left-right semantic-phonetic compound allows more effective extraction of pronunciation hints. In addition, radicals that should be interpreted together are closer spatially in the GeoD representation, making the knowledge representation easier to learn. Note that the GeoD representation is lossless as the original logograph can be reconstructed perfectly (details in Appendix A). Figure 1 shows the geometric decomposition of the Han logograph “admire” at three levels of granularity.

**Neural pronunciation prediction models**

Figure 2 and Figure 3 show two neural pronunciation prediction models of logographs. In Figure 2, each logograph is treated as an ordered “bag of radicals” (BoR). For example, assume the vocabulary of radicals in the whole dataset is \{⿰,忄,氵,灬, 耳\}, the word "admire" ("admire" - see Figure 1) is represented by a vector of counts \{1, 0, 3, 0\}, corresponding to one radical \(\uparrow\) and three radicals 耳.

The BoR is input to a multilayer perceptron (MLP) with three layers of size 750, 500, 250. L2 regularization of 1e-4 is applied to the hidden layers. The three dropout layers have dropout probabilities of 0.5, 0.5, and 0.2, respectively. As the output variables are categorical, cross-entropy loss was used.

We investigated two structures for predicting output phonemes (i.e. onset, nucleus, coda). In the first structure, output phonemes were predicted independently using the last hidden layer. The second structure made a sequential prediction (1) the coda was first predicted using the last hidden layer (2) the nucleus was predicted using both the final hidden layer and the predicted coda, and (3) the onset was predicted using the last hidden layer together with the predicted coda and nucleus. The second structure was motivated by a stronger dependency between the nuclues and coda. For example, the nucleus and coda are often grouped together as a single unit (rime/final) in the syllabic structure of most languages (Kessler and Treiman, 2002). In our experiments, the sequential structure yielded lower error rates so it is used in all neural network models.

**Figure 2**: Pronunciation model of logographs using multilayer perceptron (MLP). FC: Fully connected.

In Figure 3, each logograph is represented by its geometric decomposition (GeoD). For example, the logograph 懾 is represented by a sequence of radicals and geometric operators shown in Figure 1C. The neural prediction model consists of two LSTM layers with 256 memory cells each. Input and recurrent dropout (Gal and Ghahramani, 2016) of 0.2 and 0.5 are applied to the LSTM layers to prevent overfitting.
Multimodal neural pronunciation model of logographs

In this section, we want to model the pronunciations of a logograph in the target language Cantonese using multimodal information from both the logograph and phonemes of the cognates, as shown in Figure 4. Given a vocabulary of phonemes in the source languages related to Cantonese (Mandarin, Korean, Vietnamese), the cognates’ phonemes are encoded as an indicator vector, with an element equals 1 if the corresponding phoneme in the vocabulary appears in a cognate’s pronunciation, and 0 otherwise.

The geometric decomposition (GeoD) of the logograph is fed to two LSTM layers. The output at the last time step is concatenated together with the multilingual phonemic vector and used as input for a multi-layer perceptron (MLP). The MLP and LSTM setups are the same as those in Figure 2 and Figure 3 respectively. Deep supervision (Szegedy et al., 2015) was applied by using the output of the LSTM to make auxiliary prediction of the output phonemes. Note that the auxiliary prediction should be identical to the main prediction. While predicting the same target, the main prediction used both cognate phonemes and the logograph while the auxiliary prediction used only the logograph. This was to ensure features extracted from the logographs are useful for pronunciation prediction and are complementary to the features extracted from the multilingual phonemes.

4 Experiments

We investigate whether Cantonese phonemes could be predicted using Han logographs and the cognates’ phonemes from Mandarin, Korean, and Vietnamese. The prediction output are Cantonese onsets, nuclei and codas. The experimental design is motivated by the nature of Han-logographic languages. A Chinese logograph (character) is phonologically equivalent to a syllable in English while the constituent radicals are analogous to alphabet letters (with far less phonetic information). While in most languages, a syllable’s pronunciation is influenced by neighboring syllables, most Han-logographic languages are monosyllabic and a logograph’s pronunciation is rarely affected by neighboring logographs. Therefore, pronunciation prediction at the logograph (character) level for Han logographs is more appropriate. We use string error rate (SER) and token error rate (TER) as evaluation metrics. A wrongly predicted phoneme (onset, nucleus or coda) is counted as one token error. A syllable containing token error(s) is counted as one string error. All the neural networks were trained using Adam (Kingma and Ba, 2014).

Data

The dataset is extracted from the UniHan database, which is a pronunciation database of logographs from Han logographic languages and maintained by the Unicode consortium. For each entry in the dataset, a logograph corresponds to phonemes in Cantonese, Mandarin, Korean and Vietnamese, represented by Jyutping, Pinyin, Yale, and Vietnamese alphabet symbols respectively. We randomly partition the dataset into two sets, with 80% for training and the other 20% for testing. Overall, there are 16,011 entries in the training set and 4,002 entries in the test set. 1000 entries of the training set are used as the development set for hyper-parameters fine-tuning.

In the test set, only 16% of logographs have pronunciations in all non-target languages, while 6% of logographs have no non-target language pronunciation. The availability of pronunciations in non-target languages differs from logograph to logograph. For example, some logographs have Mandarin and Korean pronunciations, while others only have Mandarin pronunciations.

Predicting pronunciation using logograph input

We compared the neural networks against a decision tree baseline. The decision tree baseline was implemented using scikit-learn (Pedregosa et al., 2011). The input of the decision tree (DT) model is the BoR representation of the logograph, while the input of neural networks can be either BoR or GeoD. The MLP network in Figure 2 uses BoR, while the LSTM in Figure 3 uses GeoD as input. All models output phonemes in Cantonese.

From Table 2, the neural network (MLP) outperforms decision tree when using BoR input. Both the SER and TER of the MLP model are lower than those of the decision tree. The LSTM model using GeoD leads to the lowest SER and TER, suggesting the benefits of relative positional

3https://www.unicode.org/charts/unihan.html
4https://en.wikipedia.org/wiki/Jyutping
5https://en.wikipedia.org/wiki/Pinyin
6https://en.wikipedia.org/wiki/Yale
7https://en.wikipedia.org/wiki/Vietnamese_alphabet
information of radicals in predicting pronunciation. The trends of onset, nucleus and coda error rates are similar to those of TER and SER. However, as the gap of error rate between MLP (BoR) and LSTM (GeoD) for TER and SER are quite small, using BoR instead of GeoD can be a good computation-accuracy trade-off.

| Method               | SER  | TER  | On.  | Nu.  | Cd.  |
|----------------------|------|------|------|------|------|
| DT (BoR)             | 63.8 | 39.8 | 50.7 | 45.7 | 22.9 |
| MLP (BoR)            | 59.2 | 33.6 | 44.5 | 38.6 | 17.8 |
| LSTM (GeoD)          | 58.4 | 32.6 | 43.3 | 37.4 | 17.1 |

Table 2: Prediction error rates of Cantonese phonemes by decision tree (DT), MLP and LSTM using only logographic input. Best results are in bold.

5 Discussion

We have empirically shown that the systematic yet tenuous correspondence between pronunciations of cognates in Han logographic languages can be exploited for pronunciation modeling using neural networks. Moreover, combining logograph with cognate pronunciations further improves pronunciation prediction. These results could be potentially applied to speech processing tasks such as speech synthesis, where the construction of pronunciation dictionaries are expert labor-intensive, especially for under-resourced spoken languages.

For future work, recursive neural network (Tai et al., 2015) can be used as it is better suited for the hierarchical logographic decomposition. Besides, incorporating more detailed relationship between radicals (e.g. (Zhuang et al., 2017)) can help improve the model. The proposed approaches can also be applied to other languages such as Min Nan or Hakka, which are spoken languages that are even less well-documented than Cantonese.
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A The Ideographic Description algorithm

The Ideographic Description algorithm, defined by the Unicode Consortium, describes a way to represent a grapheme by its components. All Han logographs (i.e. graphemes) can be recursively decomposed into smaller components that are themselves logographs. With IDS denoting an logograph, the Ideographic Description algorithm can be written as

$$\text{IDS} := \text{IDS} \mid \text{BinaryOperator IDS IDS} \mid \text{TrinaryOperator IDS IDS IDS/}$$

This simply means that an logograph can be decomposed into one, two or three smaller logographs. The operators indicate the relative positions of the operands. Many logographs can be described in more than one way using this algorithm as the logographs can themselves be broken down further.

Figure S5: (reproduced from Figure 1) A, B and C are equivalent ideographic description sequences for the same logograph. Each sequence can also be represented as a tree.

Figure S5 shows three different ways the logograph for “admire” can be decomposed at different levels of granularity. The granularity depends on the set of basic logographs at which the algorithm terminates. As the algorithm is recursive, the decomposition of a logograph is a tree or a sequence with the operators evaluated in prefix order. The sequence representation is lossless as it preserves the relative geometric position between the components. The logograph can be reconstructed perfectly from the sequence of components.

Figure S5 also shows how the three sequence of components are represented as three vectors of count. Different from the sequence representation, representing the components as a vector of counts is lossy, as the geometric relationship between components are not preserved. Representing graphemes as sequences rather than as vectors may lead to higher prediction accuracy if the positional information is useful for the task.