How to Speak a Language without Knowing It

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Abstract
We develop a system that lets people overcome language barriers by letting them speak a language they do not know. Our system accepts text entered by a user, translates the text, then converts the translation into a phonetic spelling in the user’s own orthography. We trained the system on phonetic spellings in travel phrasebooks.

1 Introduction
Can people speak a language they don’t know? Actually, it happens frequently. Travel phrasebooks contain phrases in the speaker’s language (e.g., “thank you”) paired with foreign-language translations (e.g., “спасибо”). Since the speaker may not be able to pronounce the foreign-language orthography, phrasebooks additionally provide phonetic spellings that approximate the sounds of the foreign phrase. These spellings employ the familiar writing system and sounds of the speaker’s language. Here is a sample entry from a French phrasebook for English speakers:

English: Leave me alone.
French: Laissez-moi tranquille.
Franglish: Less-ay mwah trahn-KEEL.

The user ignores the French and goes straight to the Franglish. If the Franglish is well designed, an English speaker can pronounce it and be understood by a French listener.

Figure 1 shows a sample entry from another book—an English phrasebook for Chinese speakers. If a Chinese speaker wants to say “非常感谢你这顿美餐”, she need only read off the Chinglish “三可油否热斯弯德否米欧”, which approximates the sounds of “Thank you for this wonderful meal” using Chinese characters.

Phrasebooks permit a form of accurate, personal, oral communication that speech-to-speech translation devices lack. However, the user is limited to a small set of fixed phrases. In this paper, we lift this restriction by designing and evaluating a software program with the following:

- Input: Text entered by the speaker, in her own language.
- Output: Phonetic rendering of a foreign-language translation of that text, which, when pronounced by the speaker, can be understood by the listener.

The main challenge is that different languages have different orthographies, different phoneme inventories, and different phonotactic constraints, so mismatches are inevitable. Despite this, the system’s output should be both unambiguously pronounceable by the speaker and readily understood by the listener.

Our goal is to build an application that covers many language pairs and directions. The current paper describes a single system that lets a Chinese person speak English.

We take a statistical modeling approach to this problem, as is done in two lines of research that are most related. The first is machine transliteration (Knight and Graehl, 1998), in which names and technical terms are translated across languages with different sound systems. The other is re-spelling generation (Hauer and Kondrak, 2013), where an English speaker is given a phonetic hint about how to pronounce a rare or foreign word to another English speaker. By contrast, we aim
to help people issue full utterances that cross language barriers.

2 Evaluation

Our system’s input is Chinese. The output is a string of Chinese characters that approximate English sounds, which we call Chinglish. We build several candidate Chinese-to-Chinglish systems and evaluate them as follows:

- We compute the normalized edit distance between the system’s output and a human-generated Chinglish reference.
- A Chinese speaker pronounces the system’s output out loud, and an English listener takes dictation. We measure the normalized edit distance against an English reference.
- We automate the previous evaluation by replace the two humans with: (1) a Chinese speech synthesizer, and (2) a English speech recognizer.

3 Data

We seek to imitate phonetic transformations found in phrasebooks, so phrasebooks themselves are a good source of training data. We obtained a collection of 1312 <Chinese, English, Chinglish> phrasebook tuples (see Table 1).

We use 1182 utterances for training, 65 for development, and 65 for test. We know of no other computational work on this type of corpus.

Our Chinglish has interesting gross empirical properties. First, because Chinglish and Chinese are written with the same characters, they render the same inventory of 416 distinct syllables. However, the distribution of Chinglish syllables differs a great deal from Chinese (Table 2). Syllables “si” and “te” are very popular, because while consonant clusters like English “st” are impossible to reproduce exactly, the particular vowels in “si” and “te” are fortunately very weak.

| Frequency Rank | Chinese | Chinglish |
|----------------|---------|-----------|
| 1              | de      | si        |
| 2              | shi     | te        |
| 3              | yi      | de        |
| 4              | ji      | yi        |
| 5              | zhi     | fu        |

Table 2: Top 5 frequent syllables in Chinese (McEnery and Xiao, 2004) and Chinglish

We find that multiple occurrences of an English word type are generally associated with the same Chinglish sequence. Also, Chinglish characters do not generally span multiple English words. It is reasonable for “can I” to be rendered as “kan nai”, with “nai” spanning both English words, but this is rare.

4 Model

We model Chinese-to-Chinglish translation with a cascade of weighted finite-state transducers (wFST), shown in Figure 2. We use an online MT system to convert Chinese to an English word sequence (Eword), which is then passed through FST A to generate an English sound sequence (Epron). FST A is constructed from the CMU Pronouncing Dictionary (Weide, 2007).

Next, wFST B translates English sounds into Chinese sounds (Pinyin-split). Pinyin is an official syllable-based romanization of Mandarin Chinese characters, and Pinyin-split is a standard separation of Pinyin syllables into initial and final parts. Our wFST allows one English sound token to map
to one or two Pinyin-split tokens, and it also allows two English sounds to map to one Pinyin-split token.

Finally, FST C converts Pinyin-split into Pinyin, and FST D chooses Chinglish characters. We also experiment with an additional wFST E that translates English directly into Chinglish.

5 Training

FSTs A, C, and D are unweighted, and remain so throughout this paper.

5.1 Phoneme-based model

We must now estimate the values of FST B parameters, such as $P(s_i|s)$. To do this, we first take our phrasebook triples and construct sample string pairs <Epron, Pinyin-split> by pronouncing the phrasebook English with FST A, and by pronouncing the phrasebook Chinglish with FSTs D and C. Then we run the EM algorithm to learn FST B parameters (Table 3) and Viterbi alignments, such as:

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c}
    g & r & ae & n & d & m & ah & dh & er \\
    ge & r & an & de & mu & e & d & e \\
\end{array}
\]

where as the reference Pinyin-split sequence is:

\[
\text{g e r uan d e m a d e}
\]

Here, “ae n” should be decoded as “uan” when preceded by “r”. Following phrase-based methods in statistical machine translation (Koehn et al., 2003) and machine transliteration (Finch and Sumita, 2008), we model substitution of longer sequences. First, we obtain Viterbi alignments using the phoneme-based model, e.g.:

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c}
    g & r & ae & n & d & m & ah & dh & er \\
    ge & r & uan & de & mu & e & d & e \\
\end{array}
\]

Second, we extract phoneme phrase pairs consistent with these alignments. We use no phrase-size limit, but we do not cross word boundaries. From the example above, we pull out phrase pairs like:

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c}
    g & r & ae & n & d & m & ah & dh & er \\
    ge & r & an & de & mu & e & d & e \\
\end{array}
\]

We add these phrase pairs to FST B, and call this the phoneme-phrase-based model.

5.3 Word-based model

We now turn to wFST E, which short-cuts directly from English words to Pinyin. We create <English, Pinyin> training pairs from our phrasebook simply by pronouncing the Chinglish with FST D. We initially allow each English word type to map to any sequence of Pinyin, up to length 7, with uniform probability. EM learns values for parameters like $P(\text{nai te}|\text{night})$, plus Viterbi alignments such as:

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c}
    g & r & ae & n & d & m & ah & dh & er \\
    ge & r & an & de & mu & e & d & e \\
\end{array}
\]
| Model                          | Top-1 Overall Average Edit Distance | Top-1 Valid Average Edit Distance | Coverage |
|-------------------------------|------------------------------------|----------------------------------|----------|
| Word based                    | 0.664                              | 0.042                            | 29/65    |
| Word-based hybrid training    | 0.659                              | 0.029                            | 29/65    |
| Phoneme based                 | 0.611                              | 0.583                            | 63/65    |
| Phoneme-phrase based          | 0.194                              | 0.136                            | 63/65    |
| Hybrid training and decoding  | 0.175                              | 0.115                            | 63/65    |

Table 4: English-to-Pinyin decoding accuracy on a test set of 65 utterances. Numbers are average edit distances between system output and Pinyin references. Valid average edit distance is calculated based only on valid outputs (e.g. 29 outputs for word based model).

Notice that this model makes alignment errors due to sparser data (e.g., the word “tips” and “ti pu si” only appear once each in the training data).

5.4 Hybrid training

To improve the accuracy of word-based EM alignment, we use the phoneme based model to decode each English word in the training data to Pinyin. From the 100-best list of decodings, we collect combinations of start/end Pinyin syllables for the word. We then modify the initial, uniform English-to-Pinyin mapping probabilities by giving higher initial weight to mappings that respect observed start/end pairs. When we run EM, we find that alignment errors for “tips” in section 5.3 are fixed:

accept a ke sha pu | tips te ti pu si

Table 6: Unseen English word type and tokens in test data.

5.5 Hybrid decoding

The word-based model can only decode 29 of the 65 test utterances, because wFST E fails if an utterance contains a new English word type, previously unseen in training. The phoneme-based models are more robust, able to decode 63 of the 65 utterances, failing only when some English word type falls outside the CMU pronouncing dictionary (FST A).

Our final model combines these two, using the word-based model for known English words, and the phoneme-based models for unknown English words.

6 Experiments

Our first evaluation (Table 4) is intrinsic, measuring our Chinglish output against references from the test portion of our phrasebook, using edit distance. Here, we start with reference English and measure the accuracy of Pinyin syllable production, since the choice of Chinglish character does not affect the Chinglish pronunciation. We see that the Word-based method has very high accuracy, but low coverage. Our best system uses the Hybrid training/decoding method. As Table 6 shows, the ratio of unseen English word tokens is small, thus large portion of tokens are transformed using word-based method. The average edit distance of phoneme-phrase model and that of hybrid training/decoding model are close, indicating that long phoneme-phrase pairs can emulate word-pinyin mappings.

Table 7: Chinglish-to-English accuracy in dictation task.
Table 5: Chinglish generated by hybrid training and decoding method and corresponding recognized English by dictation and automatic synthesis-recognition method.

| Chinese                           | Reference English                                  |
|----------------------------------|---------------------------------------------------|
| 年夜饭都要吃些什么                | what do you have for the Reunion dinner            |
| Reference Chinglish              | 沃特杜文海夫佛则锐文尼恩低呢                      |
| Hybrid training/decoding Chinglish| 我忒度优嗨佛得瑞优你恩低呢                      |
| Dictation English                | what do you have for the reunion dinner            |
| ASR English                      | what do you high for 43 Union Cena                 |
| Chinese                          | 等等我                                             |
| Reference English                | wait for me                                        |
| Reference Chinglish              | 唯特佛密 (wei te fo mi)                             |
| Hybrid training/decoding Chinglish| 位特佛密 (wei te fo mi)                           |
| Dictation English                | wait for me                                        |
| ASR English                      | wait for me                                        |

Table 8: Chinglish-to-English accuracy in automatic synthesis-recognition (ASR) task. Numbers are average edit distance between recognized English and reference English.

| Model                               | Valid Average Edit Distance |
|-------------------------------------|-----------------------------|
| Word based                          | 0.925                       |
| Word-based hybrid training          | 0.925                       |
| Phoneme based                       | 0.937                       |
| Phoneme-phrase based                | 0.896                       |
| Hybrid training and decoding        | 0.898                       |

Finally, we repeat the last experiment, but removing the human from the loop, using both automatic Chinese speech synthesis and English speech recognition. Results are shown in Table 8. Speech recognition is more fragile than human transcription, so edit distances are greater. Table 5 shows a few examples of the Chinglish generated by the hybrid training and decoding method, as well as the recognized English from the dictation and ASR tasks.

7 Conclusions

Our work aims to help people speak foreign languages they don’t know, by providing native phonetic spellings that approximate the sounds of foreign phrases. We use a cascade of finite-state transducers to accomplish the task. We improve the model by adding phrases, word boundary constraints, and improved alignment.

In the future, we plan to cover more language pairs and directions. Each target language raises interesting new challenges that come from its natural constraints on allowed phonemes, syllables, words, and orthography.

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