A Pointwise Approach to Pronunciation Estimation for a TTS Front-end

Shinsuke Mori, Graham Neubig

Kyoto University, School of Informatics

forest@i.kyoto-u.ac.jp, neubig@ar.media.kyoto-u.ac.jp

Abstract

In this paper, we propose a pointwise approach to the Japanese TTS front-end. In this approach, phoneme sequence estimation of sentences is decomposed into two tasks: word segmentation of the input sentence and phoneme estimation of each word. Then these two tasks are solved by pointwise classifiers without referring to the neighboring classification results.

In contrast to existing sequence-based methods, an n-gram model based on sequences of word-phoneme pairs for example, this framework enables us to use various language resources such as sentences in which only a few words are annotated, or an unsegmented list of compound words, among others.

In the experiments, we compared a joint tri-gram model with the combination of a pointwise word segmenter and a pointwise phoneme sequence estimator. The results showed that our framework successfully enables a TTS front-end to refer to a partially annotated corpus and/or a word sequence list annotated with phoneme sequences to realize a far larger improvement in accuracy.

1. Introduction

A text-to-speech (TTS) system consists of two modules. One is a front-end, which takes a sentence as its input and returns a phoneme sequence annotated with accent information of the sentence. The other is a back-end, which converts the output of a front-end into sound. For a front-end, the vital part is phoneme sequence estimation, as the intelligibility depends on its correctness. To estimate the correct phoneme sequence of a sentence, we need to recognize words and determine their phoneme sequences.

For English, there have been attempts at solving this problem by neural networks [1]. In English there are few words of multiple pronunciations, such as *read*, and they can be easily distinguished by their part-of-speech information, the research focus has been shifted to so-called G2P, phoneme sequence estimation from graphemes especially for unknown words [2] [3]. In some languages such as Finnish, Turkish, and Korean, character sequences, which are separated by whitespaces, are combinations of prefixes, a stem, and suffixes, so they are not be able to be covered with an ordinary vocabulary. To cope with this problem, there is data-driven research for these languages such as [4], which describes a data-driven method for Korean language pronunciation estimation.

In some other languages such as Japanese or Chinese, which we focus on in this paper, there is no whitespace between words. Thus for phoneme sequence estimation of a sentence in these languages, we must segment the input sentence into words and annotate them with phoneme sequences. There have been some attempts at solving this problem with a joint n-gram models which use word/phoneme pairs as units [5]. This is a natural extension of a morphological analyzer based on word/part-of-speech pairs [6, 7].

This sequence-based modeling, however, requires a fully annotated corpus, a collection of sentences divided into word sequences annotated with phonemes, and is not capable of referring to a variety of language resources, such as a partially annotated corpus or a dictionary containing word sequences annotated with phonemes.

In this paper, we propose a pointwise approach to phoneme sequence estimation for Japanese. In this approach, the phoneme sequence estimation task for sentences is decomposed into two tasks: one is word segmentation of the input sentence and the other is phoneme estimation of each word. Then these two tasks are solved by pointwise classifiers without referring to the neighboring classification results. This framework allows us to use various language resources such as sentences annotated only with word boundary information or word sequences from sentences partially annotated with word boundary information and a phoneme sequences [8, 9, 10].

In the experiments, we compared a joint tri-gram model with a combination of our pointwise word segmenter and our pointwise phoneme sequence estimator. The results showed that our framework successfully enables a TTS front-end to refer to a partially annotated corpus and/or a compound word list with a phoneme sequence to realize further improvement in accuracy.

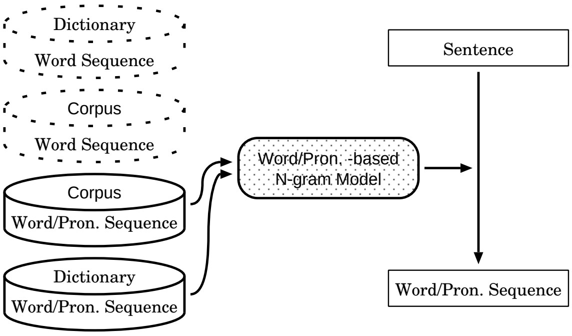
2. A Data-driven Approach to TTS Front-end

As described in the previous section, a front-end of a TTS system for Japanese has to solve the word segmentation problem and phoneme sequence estimation for segmented words. In this section, we describe the joint n-gram approach [5, 2, 3], as a representative of the existing data-driven methods.

2.1. Front-end Based on a Joint N-gram Model

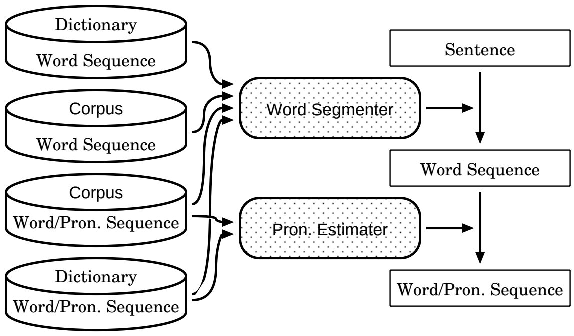
A statistical morphological analyzer [6] takes word/part-of-speech (POS) pairs as the unit of a joint n-gram model and searches for the word-POS pair sequence with the highest generative probability for a given sentence, under the condition that the concatenation of the words in the sequence is equal to the input sentence. Inspired by this research, a TTS front-end based on the same framework has been proposed in [5]. This research proposes to use pairs of a word w and its phoneme sequence $\boldsymbol{y}$ as the unit of an n-gram model, $u = \langle w, \boldsymbol{y} \rangle$[1]. Then the probability of a unit sequence $\boldsymbol{u} = u_1 u_2 \cdots u_h$ by an n-gram model

[1] In the original paper [5], a quadruplet of spelling of a word, its POS, its phoneme sequence, and its accent sequence is used.



Corpora must be fully annotated.

Figure 1: The sequence-based approach.



Partially annotated corpora are also available.

Figure 2: The pointwise approach.

$M_{n,u}$ is computed as follows:

$$M_{n,u}(u_1 u_2 \cdots u_h) = \prod_{i=1}^{h+1} P(u_i | u_{i-n+1} \cdots u_{i-2} u_{i-1}). \quad (1)$$

where u_i $(i \leq 0)$ is a special symbol indicating the beginning of the sentence, and u_{h+1} is another special symbol indicating the end of the sentence. They are introduced just for a notation simplicity.

Similarly to the morphological analyzer, the statistical front-end, given a character sequence $\boldsymbol{x} = x_1 x_2 \cdots x_{h'}$ as an input sentence, searches for the unit sequence $\hat{\boldsymbol{u}}$ with the highest probability under the constraint that the concatenation of the spellings $\boldsymbol{w} = w_1 w_2 \cdots w_h$ is equal to the input sentence:

$$\hat{\boldsymbol{u}} = \mathop{\mathbf{argmax}}_{\boldsymbol{x}=\boldsymbol{w}} M_{n,u}(u_1 u_2 \cdots u_h). \quad (2)$$

The search problem is solved efficiently using dynamic programming [11].

2.2. Unknown Word Model

In real applications, unknown words are not avoidable. To estimate a pronunciation of an unknown word, the pair-based n-gram approach [5] uses an n-gram model based on pairs of character and phoneme sequence $v = \langle x, \boldsymbol{y} \rangle$

$$M_{n,v}(u) = \prod_{i=1}^{k+1} P(v_i | v_{i-n+1} \cdots v_{i-2} v_{i-1}), \quad (3)$$

where the spelling of u is equal to $x_1 x_2 \cdots x_k$ which is the concatenation of characters of $v_1 v_2 \cdots v_k$. Note that this unknown word module is very similar to the ones proposed for English unknown words [2] [3], since one Japanese character usually corresponds to one or two syllables.

2.3. Parameter Estimation

The parameters of n-gram models $M_{n,u}$ and $M_{n,v}$ are estimated from a corpus. In the corpus, sentences must be segmented completely into words and all the words must be annotated with a phoneme sequence. This annotation work is costly, especially considering domain adaptation. In an adaptation situation, we need annotators who know the segmentation standard well, for example, a sequence of a verbal stem and its ending followed by a sequence of auxiliary verb expressions and the pronunciations of special place names or technical terms in the medical domain. Putting it in another way, in an adaptation situation, we need to find specialists who are familiar with the target domain and the annotation standard at the same time. So we need a framework which allows us an easy and fast adaptation.

3. A Pointwise Approach

As we pointed out in the previous section, sequence-based methods require fully annotated training sentences, which are very costly to prepare. In order to overcome this shortcoming, we propose a pointwise approach, in which the phoneme sequence estimation task of a sentence is divided into two steps as shown in Figure 2:

1. Word Segmentation (WS): Dividing an unspaced character string into appropriate units.
2. Pronunciation Estimation (PE): Estimation of the pronunciation of each segmented unit[2].

In the subsequent part, we explain WS and PE based on a pointwise classifier.

3.1. Word Segmentation for a Sentence

The word segmentation problem is defined as putting whitespaces at all points between two characters belonging to different words and putting nothing between characters belonging to the same word according to a predefined word segmentation standard. Given an unsegmented character string $\boldsymbol{x} = x_1 x_2 \cdots x_{h'}$ as input

$$\boldsymbol{x} = \text{大分は今日は快晴です},$$

the characters are segmented into words by estimating whether a boundary between x_i and x_{i+1} exists for each i, $1 \leq i < h'$. Using this information, we can acquire a segmented word string $\boldsymbol{w}$,

$$\boldsymbol{w} = \text{大分 は 今日 は 快晴 で す}.$$

The pointwise method assumes that every decision about a segmentation point is independent from the other decisions. For example, the decision whether a word boundary lies between characters x_i and x_{i+1} can depend on any number of features based on the surrounding characters, but not on whether a boundary lies between characters x_{i-1} and x_i. Putting it in another way, the classifier uses features of input characters but not of the output tags.

We propose, as possible features of the classifier, all of the character and character type n-grams ($n \leq 3$) contained by

[2]In this paper, we use the term *pronunciation* as the same meaning of *phoneme sequence*

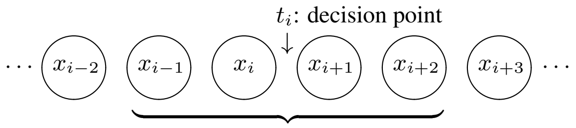


Figure 3: The characters to be referred to in word segmentation.

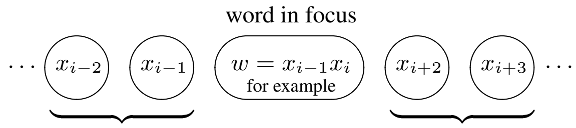


Figure 4: The characters to be referred to in pronunciation estimation of a word.

Table 1: Corpora.

usage	domain	#sents	#words	#chars
learning	balanced	33,147	899,025	1,292,249
learning	newspaper	9,023	–	398,570
test	balanced	3,681	98,634	141,655
test	newspaper	1,002	29,038	43,695

x_{i-1}^{i+2} to decide whether a boundary exists between x_i and x_{i+1} or not (see Figure 3). In addition we used the following modifications.

- The character n-grams and character type n-grams are annotated with the offset from the character boundary under consideration.

In order for our word segmenter to exploit a dictionary containing word sequences, our word segmenter also checks out whether the character n-grams with/without a word boundary at the corresponding position appear in the dictionary or not.

3.2. Pronunciation Estimation for a Word

The above word segmentation process outputs a word sequence. Then, we annotate each word in the sequence with possible phoneme sequences using the corpus and dictionaries. The example sentence becomes as follows:

> 大分/{o o i ta, da i bu} は/{ha} 今日/{kyo u, ko n ni chi} は/{ha} 快晴/{} で/{de} す/{su}.

Words with only one possible phoneme sequence (ex. は/{ha}) are annotated with that sequence. The phoneme sequence of unknown words (ex. 快晴/{}) is estimated using the same joint n-gram model in Equation (3) of Section 2.

For words with several possible phoneme sequences (ex. 大分/{o o i ta, da i bu}), we use classifiers to choose the most appropriate one among them. We prepare classifiers for all words with multiple phoneme sequence candidates. They are trained on an annotated corpus and a dictionary containing sequences of word-pronunciation pairs. Similarly to the word segmenter, the classifier is based on a pointwise method and refers only to the character and character-type n-grams ($n \leq 3$) surrounding the word (see Figure 4). Note that the classifier does not refer to word boundary information. This allows us to use a partially annotated corpus, in which only some words are annotated with word boundary information and a phoneme sequence as follows:

> 九州にある 大分/o o i ta は暖かいです

where only the word 大分 is segmented and annotated with a phoneme sequence.

After these processes, our pointwise pronunciation estimator for a word sequence outputs a string of words, each annotated with a single phoneme sequence as follows:

> 大分/o o i ta は/ha 今日/kyo u は/ha 快晴/ka i se i で/de す/su .

Table 2: Accuracy in the general domain.

Model	precision	recall
Pair tri-gram	99.07%	99.12%
Pointwise	99.19%	99.26%

4. Evaluation

As an evaluation of our framework, we measured the phoneme sequence estimation accuracies for Japanese sentences of the joint tri-gram model and the pointwise method mainly in a domain adaptation case. In this section we show the results and evaluate our new framework.

4.1. Experimental Conditions

As a general domain corpus, we used the Balanced Corpus of Contemporary Written Japanese (BCCWJ) [12] which consists of sentences extracted from various sources. We held out every 10th sentence for our test set. The sentences are segmented into words and annotated with pronunciation manually (see Table 1). The corpus in the target domain is composed of articles extracted from newspapers specialized in the economy. The test corpus in this domain, made by taking every 10th sentence, is annotated with word boundary information and each word is annotated with a phoneme sequence to measure accuracies. The learning corpus is, however, annotated partially with this information. This is used in the second part of the experiments.

As classifiers for word segmentation and phoneme sequence estimation, we use linear SVMs [13].

4.2. Evaluation Criterion

As an evaluation criterion we follow [5] and use precision and recall based on mora. First the longest common subsequence (LCS) is found between the correct answer and system output. Then let N_{REF} be the number of morae in the correct sentence, N_{SYS} be that in the output in a system, and N_{LCS} be that in the LCS of the correct sentence and the output of the system, so the recall is defined as N_{LCS}/N_{REF} and the precision as N_{LCS}/N_{SYS}. Note that $N_{LCS} = N_{REF} - N_{sub} - N_{del} = N_{SYS} - N_{sub} - N_{ins}$, where N_{sub}, N_{del}, and N_{ins} are the numbers of substitutions, deletions, and insertions, respectively.

4.3. Learning from a Fully Annotated Corpus

First we compared the accuracies in the general domain and the target domain of two methods. Table 2 shows the accuracies in the general domain and Table 3 shows those in the target domain. From a comparison between the recalls in Table 2, we see that about 16% errors in the pair tri-gram model were eliminated by our method. The difference is statistically significant with a level of 1%. Table 3 shows that the improvement is far larger in the target domain. From these results, we can say that our pointwise method outperforms the joint tri-gram method, and is particularly robust to out-of-domain text.

Table 3: Accuracy in the target domain before adaptation.

Model	precision	recall
Pair tri-gram	97.83%	97.23%
Pointwise	98.04%	97.48%

Table 4: Accuracy in the target domain. PAC stands for a partially annotated corpus and DWS stands for a dictionary of word sequences.

Model	PAC	DWS	precision	recall
Pair tri-gram	No	No	97.83%	97.23%
Pair tri-gram	Yes	Yes	98.02%	97.51%
Pointwise	No	No	98.04%	97.48%
Pointwise	Yes	No	98.27%	98.09%
Pointwise	No	Yes	98.07%	97.51%
Pointwise	Yes	Yes	98.29%	98.12%

4.4. Using Various Language Resources

One of the advantages of our framework is the ability to use various language resources, such as a partially annotated corpus, a dictionary containing words or word sequences with/without a phoneme sequence. In order to attest to this advantage experimentally, we built pointwise pronunciation estimators using the following language resources in the target domain:

PAC: a partially annotated corpus.
We annotated 1,366 words in the learning corpus in the target domain with word boundary information and phoneme sequences. They are selected by the classifier estimated from the corpus in the general domain according to active learning based on classifier uncertainty [8].

DWS: a dictionary of word sequences with phoneme sequences.
We selected 1,060 most frequent compound words in a dictionary appearing in the learning corpus in the target domain and annotated them with word boundary information and phoneme sequences. As a result the dictionary contained 1,928 words (the average length is 1.82 words).

In addition we built a joint tri-gram, referring to the additional language resources (PAC and DWS) as a part of the learning corpus. Annotated sequences are added directly to the learning corpus.

Table 4 shows the accuracies in the target domain of the pronunciation estimators built from various combinations of the language resources. By referring to the additional language resources, the joint tri-gram increased the accuracy, but it is comparable to the pointwise method without any additional language resource. By referring to the PAC or DWS, the pointwise method improves the accuracy. PAC yields, however, a much larger improvement than DWS. The reason is that PAC uses the active learning criterion to select the words to be annotated, but DWS takes only the frequencies of the compound word candidates into account. In the pointwise framework, when we use two language resources together, we obtain a further improvement and the accuracy was highest.

From the above observations, we can conclude that our pointwise framework is better than the existing pair n-gram based method and is capable of utilizing a partially annotated corpus or a word sequence list to yield a higher accuracy.

5. Conclusion

In this paper we proposed a pointwise approach to phoneme sequence estimation for a TTS front-end in Japanese. Instead of modeling a sentence as a word/phoneme-sequence pair and solving the problem simultaneously, we decomposed the task into two steps (word segmentation and pronunciation estimation) to enable us to utilize various language resources, such as partially annotated sentences or a compound word list with and without phoneme sequences. Experiments comparing an existing pair-based n-gram method and our pointwise method using the same language resources showed that our pointwise approach outperforms an existing method even when the same data are used. Then we showed that the pointwise model is capable of referring to a partially annotated corpus and/or a compound word list with a phoneme sequence to realize further improvement in accuracy. These results show that our pointwise approach is better than the existing one.

6. References

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