A procedure for unsupervised lexicon learning

Anand Venkataraman  
Speech Technology and Research Lab  
SRI International  
333 Ravenswood Ave  
Menlo Park, CA 94025

Abstract

We describe an incremental unsupervised procedure to learn words from transcribed continuous speech. The algorithm is based on a conservative and traditional statistical model, and results of empirical tests show that it is competitive with other algorithms that have been proposed recently for this task.

1. Introduction

English speech lacks the acoustic analog of blank spaces that people are accustomed to seeing between words in written text. Discovering words in continuous spoken speech then is an interesting problem that has been treated at length in the literature. The issue is also particularly prominent in the parsing of written text in languages that do not explicitly include spaces between words.

In this paper, we describe an incremental unsupervised algorithm based on a formal statistical model to infer word boundaries from continuous speech. The main contributions of this study are as follows: First, it demonstrates the applicability and competitiveness of a conservative traditional approach for a task for which nontraditional approaches have been proposed even recently (?; ?; ?; ?; ?). Second, although the model leads to the development of an algorithm that learns the lexicon in an unsupervised fashion, results of partial supervision are also presented, showing that its performance is consistent with results from learning theory.

2. Related Work

While there exists a reasonable body of literature with regard to word discovery and text segmentation, especially with respect to languages such as Chinese and Japanese, which do not explicitly include spaces between words, most of the statistically based models and algorithms tend to fall into the supervised learning category. These require the model to first be trained on a large corpus of text before it can segment its input. It is only of late that interest in unsupervised algorithms for text segmentation seems to have gained ground. In the last ANLP/NAACL joint language technology conference, ? (?; ?) proposed an algorithm to infer word boundaries from character n-gram statistics of Japanese Kanji strings. For example, a decision to insert a word boundary between two characters is made solely based on whether character n-grams adjacent to the proposed boundary are relatively more frequent than character n-grams that straddle it. However, even this algorithm is not truly unsupervised. There is a threshold parameter involved that must be tuned in order to get optimal segmentations when single character words are present. Also, the number of orders of n-grams that are significant in the segmentation decision making process is a tunable parameter. The authors state that these parameters can be set with a very small number of pre-segmented training examples, as a consequence of which they call their algorithm mostly unsupervised. A further factor contributing to the incommensurability of their algorithm with our approach is that it is not immediately obvious how to adapt their algorithm to operate incrementally. Their procedure is more suited to batch segmentation, where corpus n-gram statistics can be obtained during a first pass and segmentation decisions made during the second. Our algorithm, however, is purely incremental and unsupervised and does not need to make multiple passes over the data, nor require tunable parameters to be set from training data beforehand. In this respect, it is most similar to Model Based Dynamic Programming, hereafter referred to as MBDP-1, which has been proposed in (?). To the

\[1\] See, for example, ? (?; ?; ?) for a survey and ? (?; ?) for the most recent such approach.
The language model described here is fairly standard in nature. The interested reader is referred to \( \text{?} \) (\( \text{?} \), p.57–78), where a detailed exposition can be found. Basically, we seek

\[
W = \arg \max_w P(W)
\]

\[
= \arg \max_w \prod_{i=1}^{n} P(w_i|w_1, \ldots, w_{i-1})
\]

\[
= \arg \min_w \sum_{i=1}^{n} -\log P(w_i|w_1, \ldots, w_{i-1})
\]

where \( W = w_1, \ldots, w_n \) denotes a particular string of \( n \) words. Each word is assumed to be made up of a finite sequence of characters representing phonemes from a finite inventory.

We make the unigram approximation that word histories are irrelevant to their probabilities. This allows us to rewrite the right-hand side of Equation 3 as unconditional probabilities. We also employ back-off (?1) using the Witten-Bell technique (?2) when novel words are encountered. This enables us to use an open vocabulary and estimate familiar word probabilities from their relative frequencies in the observed corpus while backing off to the letter level for novel words. In our case, a novel word is decomposed into its constituent phonemes and its probability is then calculated as the normalized product of its phoneme probabilities. To do this, we introduce the sentinel phoneme ‘\( \# \)’, which is assumed to terminate every word. The model can now be summarized very simply as follows:

\[
P(w) = \begin{cases} 
\frac{C(w)}{N^{S}P_{\Sigma}(w)} & \text{if } C(w) > 0 \\
0 & \text{otherwise}
\end{cases}
\]

\[
P_{\Sigma}(w) = \frac{r(\#)^{|w|}}{1-r(\#)}
\]

where \( C() \) denotes the count or frequency function, \( N \) denotes the number of distinct words in the word table, \( S \) denotes the sum of their frequencies, \( |w| \) denotes the length of word \( w \), excluding the sentinel ‘\( \# \)’, \( w[j] \) denotes its \( j \)th phoneme, and \( r(\#) \) denotes the relative frequency function. The normalization by dividing using \( 1-r(\#) \) in Equation 6 is necessary because otherwise

\[
\sum_{w} P(w) = \sum_{i=1}^{\infty} (1-P(\#))^i P(\#)
\]

\[
= 1 - P(\#)
\]
Since we estimate $P(w[j])$ by $r(w[j])$, dividing by $1 - r(\#)$ will ensure that $\sum_w P(w) = 1$.

4. Method

As in \(^7\), the model described in Section \(3\) is presented as an incremental learner. The only knowledge built into the system at start-up is the phoneme table with a uniform distribution over all phonemes, including the sentinel phoneme. The learning algorithm considers each utterance in turn and computes the most probable segmentation of the utterance using a Viterbi search \(^?\) implemented as a dynamic programming algorithm described shortly. The most likely placement of word boundaries computed thus is committed to before considering the next presented utterance. Committing to a segmentation involves learning word probabilities as well as phoneme probabilities from the inferred words. These are used to update their respective tables. To account for effects that any specific ordering of input utterances may have on the segmentations that are output, the performance of the algorithm is averaged over 1000 runs, with each run receiving as input a random permutation of the input corpus.

The input corpus

The corpus, which is identical to the one used by \(^?\) \(^?\), consists of orthographic transcripts made by \(^?\) \(^?\) from the CHILDES collection \(^?\). The speakers in this study were nine mothers speaking freely to their children, whose ages averaged 18 months (range 13–21). Brent and his colleagues also transcribed the corpus phonemically (using an ASCII phonemic representation), ensuring that the number of subjective judgments in the pronunciation of words was minimized by transcribing every occurrence of the same word identically. For example, “look”, “drink” and “doggie” were always transcribed “lUk”, “drINk” and “dOgi” regardless of where in the utterance they occurred and which mother uttered them in what way. Thus transcribed, the corpus consists of a total of 9790 such utterances and 33,399 words including one space after each word and one newline after each utterance.

It is noteworthy that the choice of this particular corpus for experimentation is motivated purely by its use in \(^?\) \(^?\). The algorithm is equally applicable to plain text in English or other languages. The main advantage of the CHILDES corpus is that it allows for ready and quick comparison with results hitherto obtained and reported in the literature. Indeed, the relative performance of all the discussed algorithms is mostly unchanged when tested on the 1997 Switchboard telephone speech corpus with disfluency events removed.

5. Algorithm

The dynamic programming algorithm finds the most probable word sequence for each input utterance by assigning to each segmentation a score equal to the logarithm of its probability and committing to the segmentation with the highest score. In practice, the implementation computes the negative logarithm of this score and thus commits to the segmentation with the least negative logarithm of the probability. The algorithm is presented in recursive form in Figure \(1\) for readability. The actual implementation, however, used an iterative version. The algorithm to evaluate the back-off probability of a word is given in Figure \(2\). Essentially, the algorithm description can be summed up semi-formally as follows: For each input utterance $u$, which has either been read in without spaces, or from which spaces have been deleted, we evaluate every possible way of segmenting it as $u = u' + w$ where $u'$ is a subutterance from the beginning of the original utterance up to some point within it and $w$, the lexical difference between $u$ and $u'$, is treated as a word. The subutterance $u'$ is itself evaluated recursively using the same algorithm. The base case for recursion when the algorithm re-winds is obtained when a subutterance cannot be split further into a smaller component subutterance and word, that is, when its length is zero. Suppose for example, that a given utterance is $abcde$, where the letters represent phonemes. If $\text{seg}(x)$ represents the best segmentation of the utterance $x$ and $\text{word}(x)$ denotes that $x$ is treated as a word, then

\[
\text{seg}(abcde) = \text{best of } \begin{cases} 
\text{word}(abcde) \\
\text{seg}(a) + \text{word}(bcde) \\
\text{seg}(ab) + \text{word}(cde) \\
\text{seg}(abc) + \text{word}(de) \\
\text{seg}(abcd) + \text{word}(e)
\end{cases}
\]

The evalUtterance algorithm in Figure \(3\) does precisely this. It initially assumes the entire input utterance to be a word on its own by assuming a single segmentation point at its right end. It then compares the log probability of this segmentation successively to the log probabilities of segmenting it into all possible subutterances, word pairs. Once the best segmentation into words has been found, then spaces are inserted into the utterance at the inferred points and the segmented utterance is printed out.

The implementation maintains two separate tables internally, one for words and one for phonemes. When the procedure is initially started, the word table is empty. Only the phoneme table is populated with
equipossible phonemes. As the program considers each utterance in turn and commits to its best segmentation according to the evalUtterance algorithm, the two tables are updated correspondingly. For example, after some utterance “abcde” is segmented into “a bc de”, the word table is updated to increment the frequencies of the three entries “a”, “bc” and “de” each by 1, and the phoneme table is updated to increment the frequencies of each of the phonemes in the utterance including one sentinel for each word inferred. Of course, incrementing the frequency of a currently unknown word is equivalent to creating a new entry for it with frequency 1.

5.1 Algorithm: evalUtterance

BEGIN
Input (by ref) utterance u[0..n]
where u[i] are the characters in it.

bestSegpoint := n;
bestScore := evalWord(u[0..n]);
for i from 0 to n-1; do
  subUtterance := copy(u[0..i]);
  word := copy(u[i+1..n]);
  score := evalUtterance(subUtterance) + evalWord(word);
  if (score < bestScore); then
    bestScore = score;
    bestSegpoint := i;
  fi
done
insertWordBoundary(u, bestSegpoint)
return bestScore;
END

Figure 1. Recursive optimization algorithm to find the best segmentation of an input utterance using the language model described in this paper.

One can easily see that the running time of the program is $O(mn^2)$ in the total number of utterances ($m$) and the length of each utterance ($n$), assuming an efficient implementation of a hash table allowing nearly constant lookup time is available. A single run over the entire corpus typically completes in under 10 seconds on a 300 MHz i686-based PC running Linux 2.2.5-15. Although all the discussed algorithms tend to complete within one minute on the reported corpus, MBDP-1’s running time is quadratic in the number of utterances, while the language model presented here enables computation in almost linear time. The typical running time of MBDP-1 on the 9790-utterance corpus averages around 40 seconds per run on a 300 MHz i686 PC while the algorithm described in this paper averages around 7 seconds.

5.2 Function: evalWord

BEGIN
Input (by reference) word w[0..k]
where w[i] are the phonemes in it.

score := 0;
N := number of distinct words;
S := sum of their frequencies;
if freq(word) == 0; then {
  escape := N/(N+S);
P_0 := relativeFrequency('#');
  score := -log(esc) -log(P_0/(1-P_0));
  for each w[i]; do
    score -= log(relativeFrequency(w[i]));
  done
} else {
  P_w := frequency(w)/(N + S);
  score := -log(P_w);
}
return score;
END

Figure 2. The function to compute $-\log P(w)$ of an input word $w$. If the word is novel, then the function backs off to using a distribution over the phonemes in the word.

6. Results and Discussion

In line with the results reported in ? (?), three scores were calculated — precision, recall and lexicon precision. Precision is defined as the proportion of predicted words that are actually correct. Recall is defined as the proportion of correct words that were predicted. Lexicon precision is defined as the proportion of words in the predicted lexicon that are correct. Precision and recall scores were computed incrementally and cumulatively within scoring blocks, each of which consisted of 100 utterances. We emphasize that the segmentation itself proceeded incrementally, on an utterance-by-utterance basis. Only the scores are reported on a per-block basis for brevity. These scores were computed and averaged only for the utterances within each block scored and thus they represent the performance of the algorithm on the block of utterances scored, occurring in the exact context among the other scoring blocks. Lexicon scores carried over blocks cumulatively. As Figures 3 through 5 show, the performance of our algorithm matches that of MBDP-1 on all grounds. In fact, we found to our surprise that the performances of both algorithms were almost identical except in a few instances, discussion of which space does not permit here.

This leads us to suspect the two, substantially different, statistical models may essentially be capturing the same nuances of the domain. Although ? (?) explicitly states that probabilities are not estimated for words, it turns out that considering the entire corpus
Figure 3. Word discovery precision as a function of number of utterances considered. Each scoring block (checkpoint) consists of 10% of the total number of utterances (roughly 1000). It is hard to discern two separate plots above because of the close match in their performance. 1-gram denotes the performance of the procedure reported in this paper whereas MBDP denotes the performance of Brent’s Model Based Dynamic Programming algorithm.

as a single event in probability space does end up having the same effect as estimating probabilities from relative frequencies as our statistical model does. The relative probability of a familiar word is given in Equation 22 of ? (7) as

\[ \frac{f_k(\hat{k})}{k} \cdot \left( \frac{f_k(\hat{k}) - 1}{f_k(\hat{k})} \right)^2 \]

where \( k \) is the total number of words and \( f_k(\hat{k}) \) is the frequency at that point in segmentation of the \( \hat{k} \)th word. It effectively approximates to the relative frequency

\[ \frac{f_k(\hat{k})}{k} \]

as \( f_k(\hat{k}) \) grows. The language model presented in this paper explicitly claims to use this specific estimator for the word probabilities. From this perspective, both MBDP-1 and the present model tend to favor the segmenting out of familiar words that do not overlap. In this context, we are curious to see how the algorithms would fare if in fact the utterances were favorably ordered, that is, in order of increasing length. Clearly, this is an important advantage for both algorithms. The results of experimenting with a generalization of this situation, where instead of ordering the utterances favorably, we treat an initial portion of the corpus as a training component effectively giving the algorithms free word boundaries after each word, are presented in Section 3.

In contrast with MDBP-1, we note that the model proposed in this paper has been entirely developed along conventional lines and has not made the somewhat radical assumption of treating the entire observed corpus as a single event in probability space. Assuming that the corpus consists of a single event requires the explicit calculation of the probability of the lexicon in order to calculate the probability of any single segmentation. This calculation is a nontrivial task since one has to sum over all possible orders of words in the lexicon, \( L \). This fact is recognized in ? (7), where the expression for \( P(L) \) is derived in Appendix 1 of his paper as an approximation. One can imagine then that it will be correspondingly more difficult to extend the language model in ? (7) past the case of unigrams. As a practical issue, recalculating lexicon probabilities before each segmentation also increases the running
time of an implementation of the algorithm.

Furthermore, the language model presented in this paper estimates probabilities as relative frequencies using the commonly used back-off procedure and so they do not assume any priors over integers. However, MBDP-1 requires the assumption of two distributions over integers, one to pick a number for the size of the lexicon and another to pick a frequency for each word in the lexicon. Each is assumed such that the probability of a given integer \( P(i) \) is given by \( \frac{\alpha}{\pi(i)\alpha} \). We have since found some evidence suggesting that the choice of a particular prior does not have any significant advantage over the choice of any other prior. For example, we have tried running MBDP-1 using \( P(i) = 2^{-i} \) and still obtained comparable results. It is noteworthy, however, that no such subjective prior needs to be chosen in the model presented in this paper.

The other important difference between MBDP-1 and the present model is that MBDP-1 assumes a uniform distribution over all possible word orders and explicitly derives the probability expression for any particular ordering. That is, in a corpus that contains \( n \) distinct words such that the frequency in the corpus of the \( i \)th distinct word is given by \( f_k(i) \), the probability of any one ordering of the words in the corpus is

\[
\prod_{i=1}^{n_k} \frac{f_k(i)!}{k!}
\]

because the number of unique orderings is precisely the reciprocal of the above quantity. In contrast, this independence assumption is already implicit in the unigram language model adopted in the present approach. Brent mentions that there may well be efficient ways of using \( n \)-gram distributions within MBDP-1. However, the framework presented in this paper is a formal statement of a model that lends itself to such easy \( n \)-gram extensibility using the back-off scheme proposed. It is now a simple matter to include bigrams and trigrams among the tables being learned. Since back-off has already been incorporated into the model, we simply substitute for the probability expression of a word (which currently uses no history), the probability expression given its immediate history (typically \( n - 1 \) words). Thus, we use an expression like

\[
P(w|h) = \begin{cases} 
\alpha \frac{C(h,w)}{C(h)} & \text{if } C(h,w) > 0 \\
(1 - \alpha)P(w|h') & \text{otherwise}
\end{cases}
\]

where \( P(w|h) \) denotes the probability of word \( w \) conditioned on its history \( h \), normally the immediately previous 1 (for bigrams) or 2 (for trigram) words, \( \alpha \) is the back-off weight or discount factor, which we may calculate using any of a number of standard techniques, for example by using the Witten-Bell technique as we have done in this paper, \( C() \) denotes the count or frequency function of its argument in its respective table, and \( h' \) denotes reduced history, usually by one word. Reports of experiments with such extensions can, in fact, be found in a forthcoming article (?).

7. Training

Although we have presented the algorithm as an unsupervised learner, it is interesting to compare its responsiveness to the effect of training data. Here, we extend the work in ? (?) by reporting the effect of training upon the performance of both algorithms. Figures [8] and [9] plot the results (precision and recall) over the whole input corpus, that is, blocksize = \( \infty \), as a function of the initial proportion of the corpus reserved for training. This is done by dividing the corpus into two segments, with an initial training segment being used by the algorithm to learn word and phoneme probabilities and the latter actually being used as the test data. A consequence of this is that the amount of data available for testing becomes progressively smaller as the percentage reserved for training grows. So, the significance of the test would diminish correspondingly. We may assume that the plots cease to be meaningful and interpretable when more than about 75% (about 7500 utterances) of the corpus is used for training. At 0%, there is no training information for any algorithm, and the performances of the various algorithms are identical to those of the unsupervised case. We increase the amount of training data in steps of approximately 1% (100 utterances). For each training set size, the results reported are averaged over 25 runs of the experiment, each over a separate random permutation of the corpus. The motivation was both to account for ordering idiosyncrasies and to smooth the graphs to make them easier to interpret.

We interpret Figures [8] and [9] as suggesting that the performance of all the discussed algorithms can be boosted significantly with even a small amount of training. It is also noteworthy and reassuring to see that, as one would expect from results in computational learning theory (?), the number of training examples required to obtain a desired value of precision, \( p \), appears to grow with \( 1/(1-p) \).

Significance of single word utterances

The results we have obtained provide some insight into the actual learning process, which appears to be one in which rapid bootstrapping happens with very limited data. As we had remarked earlier, all the internal tables are initially empty. Thus, the very first utter-
Figure 6. Responsiveness of the algorithm to training information. The horizontal axis represents the initial percentage of the data corpus that was used for training the algorithm. This graph shows the improvement in segmentation precision with training size.

Figure 7. Improvement in segmentation recall with training size.

frequent words. If that is the case, then ums and ah are potentially useful from a cognitive point of view to a person acquiring a lexicon since these are the very events that will bootstrap his or her lexicon with the initial seed words that are instrumental in the rapid acquisition of further words.

8. Summary

In summary, we have presented a formal model of word discovery in speech transcriptions. The main advantages of this model over that of \cite{?} are, first, that the present model has been developed entirely by direct application of standard techniques and procedures in speech processing. Second, the model is easily extensible to incorporate more historical detail in the usual way. Third, the presented model makes few assumptions about the nature of the domain and remains as far as possible conservative and simple in its development. Results from experiments suggest that the algorithm performs competitively with other unsupervised techniques recently proposed for inferring words from transcribed speech. Finally, although the algorithm is originally presented as an unsupervised learner, we have shown the effect that training data has on its performance.

Future work

Other extensions being worked on include the incorporation of more complex phoneme distributions into the model. These are, namely, the biphone and triphone models. Using the lead from \cite{?}, attempts to model more complex distributions for words such as those based on template grammars and the systematic incorporation of prosodic, stress and phonotactic con-
straint information into the model are also the subject of current interest. We already have some unpublished results suggesting that biasing the segmentation using a constraint that every word must have at least one vowel in it dramatically increases segmentation precision from 67.7% to 81.8%, and imposing a constraint that words can begin or end only with permitted clusters of consonants increases precision to 80.65%.

Another avenue of current research is concerned with iterative sharpening of the language model wherein word probabilities are periodically reestimated using a fixed number of iterations of the Expectation Modification (EM) algorithm (Dempster et al., 1977). Such reestimation has been found to improve the performance of language models in other similar tasks. It has also been suggested that the algorithm could be usefully adapted to user modeling in human-computer interaction, where the task lies in predicting the most likely atomic action a computer user will perform next. However, we have as yet no results or work to report on in this area.

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