Techniques for effective vocabulary selection

Anand Venkataraman and Wen Wang

Speech Technology and Research Laboratory, SRI International
Menlo Park, California
{anand,wwang}@speech.sri.com

Abstract

The vocabulary of a continuous speech recognition (CSR) system is a significant factor in determining its performance. In this paper, we present three principled approaches to select the target vocabulary for a particular domain by trading off between the target out-of-vocabulary (OOV) rate and vocabulary size. We evaluate these approaches against an ad-hoc baseline strategy. Results are presented in the form of OOV rate graphs plotted against increasing vocabulary size for each technique.

1. Introduction

The size and performance of a language model or speech recognition system are often strongly influenced by the size of its vocabulary. Ideally, the vocabulary is small, allowing us to build compact language models, and it is matched to the target domain so that as many as possible of the domain-specific words are known to the recognition system. Compact language models generate compact word graphs that are efficient to search and domain-matched vocabularies result in fewer out-of-vocabulary (OOV) words and consequently fewer recognition errors. In a study of the effect of OOV words on the Word Error Rate (WER) of a recognition system, Rosenfeld’s 1995 work on optimizing vocabularies, attention was mainly directed at determining the effect on the OOV rate of corpus recency, size and origin. While it was found that all three factors strongly affected the OOV rate, no specific guidelines were proposed as to how to combine the vocabularies from these different corpora to choose the target vocabulary. Indeed, Rosenfeld remarks that an ad hoc approach that discounted words by 1% for every week of age of the corpus reduced the OOV rate only very slightly for vocabulary sizes in the range of 20,000 to 50,000 words.

The paucity of work on this important topic can partly be attributed to the general observation due to Zipf that with even a moderate sized vocabulary chosen wisely, one can hope to get significant lexical coverage. Yet it is desirable from the point of view of scalability, extensibility and generality to study principled methods to address this problem. In this paper, we propose three such principled methods. The goal is to select a single vocabulary from many corpora of varying origins, sizes and recencies such that the vocabulary is optimized for both size and the OOV rate in the target domain. Section 2 describes the problem. Section 3 describes the proposed techniques, and Section 4 presents the results.

2. Problem Description

The vocabulary selection problem can be briefly summarized as follows. We wish to estimate the true vocabulary counts of a partially visible corpus of in-domain text (which we call the held-out set) when a number of other fully visible corpora, possibly from different domains, are available on which to train. There is an implicit assumption that the held-out text is related to the training text and the learning task amounts to inferring this relation. The reason for learning the in-domain counts $x_i$ of words $w_i$ is so that the words may be ranked in order of priority, enabling us to plot a curve relating a given vocabulary size to its OOV rate on the held-out corpus. Therefore, it is actually sufficient to learn some monotonic function $f(x_i)$ in place of the actual $x_i$. We may assume that the counts are normalized by document length so that the amount of available data for a particular corpus is itself irrelevant to the issue at hand.

Table 1 illustrates the problem: $v_{i,j}$ are the visible counts from each of the documents $j$, for the word $w_i$, and the $x_i$ are the incomplete counts for words $w_i$ in the partially observable training corpus vocabularies, considering the observable portion of the domain text to be a sample.

Even though vocabulary selection is an important issue and the problem appears to be simple, little work exists on this topic to date. The most common approaches seem to be ad hoc in nature, typically including words from each corpus that exceed some threshold frequency. This threshold depends on intuitions about the relevance of the corpus to the target domain. In Rosenfeld’s 1995 work on optimizing vocabularies, attention was mainly directed at determining the effect on the OOV rate of corpus recency, size and origin. While it was found that all three factors strongly affected the OOV rate, no specific guidelines were proposed as to how to combine the vocabularies from these different corpora to choose the target vocabulary. Indeed, Rosenfeld remarks that an ad hoc approach that discounted words by 1% for every week of age of the corpus reduced the OOV rate only very slightly for vocabulary sizes in the range of 20,000 to 50,000 words.
domain text.

| Word | Doc 1 | ··· | Doc j | ··· | Domain text |
|------|-------|-----|-------|-----|-------------|
| w_1  | n_{1,1} | ··· | n_{1,j} | ··· | f(x_1)      |
|      |       |     |       |     |             |
| w_i  | n_{i,1} | ··· | n_{i,j} | ··· | f(x_i)      |
|      |       |     |       |     |             |

Table 1: Problem illustration. We wish to estimate some monotonically increasing function of the true counts \( x_i \) for word \( w_i \) in the partially observed domain text based on a number of fully observed out-of-domain counts \( n_{i,j} \).

Let \( x_i \) be some function \( \Phi_i \) of the known counts \( n_{i,j} \) for \( 1 \leq j \leq m \) for each of the \( m \) corpora. Then, the problem can be restated as one of learning the \( \Phi_i \) from a set of examples where

\[
x_i = \Phi_i(n_{i,1}, \ldots, n_{i,m})
\]

In the following section, we summarize three techniques for learning the \( \Phi_i \) that optimize the vocabulary for the domain from which the held-out data was drawn.

### 3. Method

For simplicity, let the \( \Phi_i \) be linear functions of the \( n_{i,j} \) and that they are independent of the particular words, \( w_i \). That is,

\[
\Phi = \Phi_i, \forall i, j.
\]

Then we can write

\[
\Phi(n_{i,1}, \ldots, n_{i,m}) = \sum_j \lambda_j n_{i,j}
\]

The problem transforms into one of learning the \( \lambda_j \). We now outline three methods to do this. The first is based on maximum likelihood (ML) count estimation, the second and third are based on document similarity measures. We evaluate each of these three methods against a fourth baseline method that they are independent of the particular words, \( w_i \), and \( \lambda_j \) as mixture coefficients for a linear interpolation. We try to choose the \( \lambda_j \) that maximize the probability of the in-domain corpus. Formally, let \( P(w_i | j) = n_{i,j} \). Our goal is to find

\[
\lambda_1, \ldots, \lambda_m = \argmax_{\lambda_1, \ldots, \lambda_m} \prod_{i=1}^{\lambda_m} \left( \sum_j \lambda_j P(w_i | j) \right)^{C(w_i)}
\]

where \( C(w_i) \) is the count of \( w_i \) in the partially observed held-out corpus and \( V \) is the set of words in the vocabulary. The \( \lambda_j \) can subsequently be estimated via the EM algorithm [5] and used to calculate the interpolated normalized counts. The procedure shown in Figure 1 for instance, is effective in rapidly computing the values of the \( \lambda_j \).

3.2. Document-similarity-based count estimation

The document-similarity-based count estimation method calculates interpolation weights from similarity measures between the held-out corpus and each of the training corpora. This similarity measure can presumably be calculated using any of a number of methods ranging from a simple Euclidean distance metric to a more sophisticated divergence measure between the observable probability distributions, such as Kullback-Liebler (KL) [6] or a symmetric variant [7].

The Euclidean distance metric is calculated as follows. Suppose we represent each document by a vector of its normalized word counts. Then, the Euclidean distance between two corpora \( C_a \) and \( C_b \), \( \Delta(C_a, C_b) \), is given by

\[
\Delta(C_a, C_b) = \sqrt{\sum_{i=1}^{\lambda_m} (n_{a,i} - n_{b,i})^2}
\]

where \( n_{a,i} \) and \( n_{b,i} \) are the normalized counts of \( w_i \) in the corpora \( a \) and \( b \), respectively.

Likewise, the KL-divergence, which we again denote as \( \Delta(C_a, C_b) \) for the sake of uniformity, is given by

\[
\Delta(C_a, C_b) = \sum_{i=1}^{\lambda_m} P(a, i) \log \frac{P(a, i)}{P(b, i)}
\]

where we interpret the normalized word counts as probabilities.

In each of the above distance calculation schemes, let \( D_j \) be the distance of the \( j \)th corpus from the held-out domain text. Then, since the relevance of a corpus to the domain is inversely related to its distance from the domain, we define

\[
\lambda_j = \frac{1}{D_j} \sum_k \frac{1}{D_k}
\]

3.3. Data sources and implementation

The experimental setup consisted of learning the optimal vocabulary to model the language of the English broadcast news. A small amount of hand-corrected closed captioned data, amounting to just under 3 hours (about 25,000 words), drawn from six half-hour broadcast news segments from January 2001, was used as the partially visible held-out data to estimate the two mixture weights \( \lambda_1 \) and \( \lambda_2 \). This held-out data is part of the corpus released by the Linguistic Data Consortium (LDC) for the National Institute of Standards and Technology (NIST) sponsored English topic detection and tracking (TDT4) task.

The training corpora were deliberately chosen to be as different from each other in character as possible. The first corpus consisted of about 18.5 million words of English newswire data covering the period July 1994 through July 1995, and was distributed by the LDC for the NIST-sponsored Hub3 1995 continuous speech recognition task. It contained text from The NY
Times News Service, LA Times, Washington Post News Service, Wall Street Journal and Reuters North American Business News. The second training corpus consisted of a closer match to the target domain and came from segments of the TDT4 dataset released by the LDC. This consisted of about 2.5 million words of closed captioned transcripts from the period November through December 2000.

Unigram counts for the training and held-out corpora were generated using language modeling tools from the SRILM [8] using Witten-Bell [9] smoothing. Estimation of the $\lambda_j$ was performed on five of the six held-out segments which we collectively refer to as the development corpus, and OOV rates were measured on the remaining segment, which we refer to as the test corpus. This procedure was repeated six times, one for each possible split of the held-out data. The results we present are averaged numbers obtained from the six splits. Where applicable, we use the subscripts “hub3” and “tdt4” to refer to parameters specific to the above corpora.

4. Results and Discussion

We examine the results of our experiments to evaluate the various methods. Figure 2 shows a plot of the OOV rate against increasing vocabulary size from 1 word to 90,000 words. This figure, which is plotted in the logarithmic scale, is only meant to show the general shape of the individual plots and for drawing some broad generalizations. For instance, we see confirmation of the common observation that the OOV rate of a given vocabulary behind that of the former, is barely visible. The Euclidean method is also likewise affected, but to a lesser degree and slightly differently. The computed distances trend to be dominated by words that are absent in the development corpus, whereas end up with very low unigram probabilities. Thus, in summing over the entire vocabulary, large negative numbers come into play which overshadow any significant contribution to the total divergence by the unigrams observed in the development corpus. We suspect therefore that we must not attach much significance to the final quantity computed by this method unless the size of the development corpus itself is substantial.

The Euclidean method is also likewise affected, but to a lesser degree and slightly differently. The computed distances tend to be dominated by words that are absent in the development corpus rather than by words that are present in it. Since the absent words form the bulk of the vocabulary, the distances computed between the various corpora and the development text, and consequently the $\lambda_j$ will all roughly be the same, as evidenced by the figures in Table 2.

5. Conclusions

We have outlined three general techniques to select an optimal vocabulary for domain-specific speech and language modeling tasks. The techniques are scalable to arbitrarily large-sized corpora and extendible to any number of corpora. Whenever reasonable amounts of training data and reliable unigram count estimates are available, we believe that the maximum-likelihood-based method we have described is a robust way to select a domain’s vocabulary especially when its size is expected to be under a certain threshold. This threshold can be expected to
Figure 3: Averaged OOV rate across the six test corpora when the vocabulary was determined by each of the four methods described in this paper. The plot shows the segment of the OOV rate curve for a vocabulary size in the range of 1,000 to 2,000 words.

| Method     | \(\lambda_{\text{tdt4}}\) | \(\lambda_{\text{hub3}}\) | \(\Delta_{\text{tdt4}}\) | \(\Delta_{\text{hub3}}\) |
|------------|-----------------|-----------------|-----------------|-----------------|
| Max Like   | 0.89            | 0.11            | n/a             | n/a             |
| Euclidean  | 0.51            | 0.49            | 1.36            | 1.44            |
| KL-Div     | 0.42            | 0.58            | 92.86           | 66.09           |
| Uniform    | 0.50            | 0.50            | n/a             | n/a             |

Table 2: Inferred interpolation weights \(\lambda_j\), along with the normalized corpus distances from the domain text for the distance-based methods. All figures are averaged across all six splits of the test data.

vary between domains and it is possible that when it is high, the choice of any particular strategy over another does not matter. However, we believe that always following a principled strategy to select the vocabulary offers the safest path.

We plan to continue to refine and evaluate the techniques presented in this paper and apply them for vocabulary selection in the English broadcast news recognition task of the NIST 2003 Hub4 evaluation.

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