Empirical Link Between Hypothesis Diversity and Fusion Performance in an Ensemble of Automatic Speech Recognition Systems

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Abstract

Diversity is crucial to reducing the word error rate (WER) when fusing multiple automatic speech recognition (ASR) systems. We present an empirical analysis linking diversity and fusion performance. We transcribed speech from the first 2012 US Presidential debate using multiple ASR systems trained with the Kaldi toolkit. We used the N-best ROVER algorithm to perform hypothesis fusion and measured N-best diversity by the average pairwise WER. We make three key observations. We first note that the WER of the fused hypothesis decreases significantly with increasing diversity of the N-best list. This decrease is greater than the decrease in WER of the oracle hypothesis in the list. N-best lists from systems trained on different data sets are the most diverse and give the lowest WER upon fusion. We then observe that the benefit of diversity depends on the choice of the fusion scheme. We show that confidence-weighted ROVER is able to better exploit diversity than un-weighted ROVER and gives lower WERs. We finally explain the above observations by a simple linear relation linking diversity to the ROVER WER. This relation depends on the fusion scheme and also reveals the tradeoff between diversity and average WER of hypotheses in the N-best list.

Index Terms: automatic speech recognition, diversity, system combination, ROVER, ensemble methods

1. Introduction

System combination is a widespread practice in automatic speech recognition (ASR) research. Many large-scale projects such as DARPA GALE [1], TRANSTAC [2], EARS [3], and CALO [4] have utilized ensembles of ASR systems. The fused ensemble system often provides lower word error rate (WER) than the individual systems and better generalization to unseen audio data. Diversity of the ASR systems is a desirable characteristic to achieve lower WER upon fusion as noted in [1–4] and other works. Figure 1 illustrates a non-diverse and a diverse 3-best list. The diverse 3-best list in Figure 1(b) contains hypotheses with complementary errors and can thus benefit more from a suitable fusion scheme.

Many works have explored formally the benefits of ensemble diversity in machine learning [5–9]. Researchers have also developed a range of methods for training diverse ASR systems, mainly guided by empirical investigations. The simplest approach is to use diverse data sets and acoustic features for training the ASR systems. Other works [10–14] use machine learning techniques such as bagging [15], boosting [16, 17] and random forests [18] to train diverse ASR systems. Breslin [19] provides a comprehensive review of these techniques. Diverse hypotheses are also prevalent in other speech and language processing tasks. These include transcription of speech data by workers on crowd-sourcing services such as Amazon Mechanical Turk [20–26]. The advantage herein is that while any single transcription by itself may not be perfect, an appropriate combination of diverse set of transcriptions can boost accuracy.

Not many previous works have explicitly addressed the link between hypothesis diversity and fusion performance despite significant interest in training and fusing diverse ASR systems. This paper empirically investigates this important link. We transcribed speech from the first 2012 US Presidential debate using multiple ASR systems trained with the Kaldi toolkit [27]. We then conducted fusion experiments using the N-best ROVER algorithm [28]. We used the average pairwise WER for estimating the diversity of an N-best list. Our key observation is that

\[
\text{ROVER WER} \approx \text{Avg. N-best WER} - \gamma \text{(N-best Diversity)}
\]  

(1)

where \(\gamma > 0\) is a constant which depends on the N-best list and the ROVER scheme used, as discussed in Section 3.1. \(-\gamma\) approximates the change in ROVER WER with a unit change in N-best diversity keeping the average N-best WER constant. The linear expression on the right-hand side of (1) provides an accurate estimate of the ROVER WER with nearly perfect correlation and extremely low mean squared error. It also shows the tradeoff between diversity and average N-best WER and explains the following observations in this paper:

1. The WER of the fused ROVER hypothesis reduces with increasing diversity of the N-best list. This decrease is greater than the decrease in WER of the oracle lowest
WER) hypothesis in the list. N-best list from a single ASR is the least diverse and gives the least reduction in WER over the 1-best WER upon fusion. N-best lists from systems trained on different data sets are the most diverse and give the greatest benefit in WER upon fusion.

2. Not all ROVER schemes are able to exploit the diversity in an N-best list. A word confidence-aware fusion gives significantly lower WER than the vanilla word frequency-based ROVER.

The next section presents details of our experimental setup - the ASR system training using Kaldi, the testing set, and the variants of the N-best ROVER algorithm we used in this paper. Section 3 discusses the experimental results and presents a detailed analysis of the impact of diversity upon fusion performance. We conclude the paper in Section 4.

2. Experimental Setup

We first give the details of the various ASR systems we trained using the Kaldi toolkit.

2.1. ASR System Training Using the Kaldi Toolkit

The Kaldi toolkit [27] provides state-of-the-art open-source tools for training ASR systems. It offers many advantages over other ASR toolkits (e.g. HTK [29] and Sphinx [30]) such as tight integration with finite state transducers (FSTs) using the OpenFST toolkit [31], generic and extensible design, Apache 2.0 license, and recipes for various standard data sets. We used data from the Wall Street Journal (WSJ) [32], the HUB4 English broadcast news [33], and the ICSI meeting [34] data sets.

We used the default Kaldi training recipe for WSJ to train all ASR systems. This recipe uses the CMU pronunciation dictionary and its phone set. It first computes Mel frequency cepstral coefficients (MFCCs) over 25 msec long speech frames with a 10 msec shift. It then trains monophone models using the Viterbi-EM algorithm. The recipe next aligns the training data using these models and uses the resulting alignments to train triphone models (M1). We used 2000 leaves for decision tree clustering and 100000 total Gaussians.

We obtained the second system (M2) by using the alignments from the M1 models to perform Linear Discriminant Analysis (LDA) and Maximum Likelihood Linear Transformation (MLLT) for increasing the discrimination between the various phones. We then discriminatively adapted the M2 acoustic models using the Maximum Mutual Information (MMI) [35] criterion which resulted in the final system (M3). Table 1 summarizes the three systems.

<table>
<thead>
<tr>
<th>ASR System</th>
<th>Training Steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>Triphone Viterbi-EM training</td>
</tr>
<tr>
<td>M2</td>
<td>M1 → LDA → MLLT</td>
</tr>
<tr>
<td>M3</td>
<td>M2 → MMI</td>
</tr>
</tbody>
</table>

Table 1: This table summarizes the training steps for the three ASR systems used in this paper for each of the WSJ, HUB4, and ICSI data sets.

2.2. First 2012 US Presidential Debate Corpus and Generic Presidential Debate Language Model

We downloaded the audio and reference transcriptions for the first 2012 United States Presidential debate between President Barack Obama (BO) and Governor Mitt Romney (MR) from the National Public Radio (NPR) website. This debate was held at the Magness Arena of the University of Denver in Denver, Colorado and was hosted by Mr. Jim Lehrer (JL). The audio is approximately 90 minutes long.

We performed speaker diarization on this audio using the system from [36] which uses voice activity detection followed by correlation-based segmentation and hierarchical clustering. This diarization system generated three clusters corresponding to JL, BO, and MR. We did not manually correct the obtained cluster labels. We then segmented the audio into clips up to 10 sec long for faster decoding. The number of utterances for JL, BO, and MR were 107, 282, and 253 respectively. We cleaned the debate transcripts by removing punctuation marks and mapping numbers to words (e.g. “$5 trillion” to “five trillion dollars”). We did not add any out-of-vocabulary (OOV) words from the transcripts to the ASR pronunciation dictionary.

Text data from the three ASR data sets is inappropriate for training the language models due to domain mismatch. We thus obtained transcripts of all US Presidential and Vice-Presidential debates from 1960-2012 excluding the testing set. These transcripts contain approximately 0.5 million words and were used to train a 4-gram LM with back-off using SRILM [37]. Table 2 gives the WER of the 1-best (Viterbi) hypothesis for each speaker in the testing set using various systems. We observe that the systems trained on the HUB4 data set perform the best. The M3 systems give the lowest WER in most cases. The debate audio, transcripts, and LM are available here.

2.3. N-best ROVER Fusion Schemes

The ROVER algorithm first aligns the hypotheses by minimizing the total cost of word insertion, deletion, and substitution needed to make all hypotheses identical. The resulting word confusion network contains a sequence of confusion bins each represented as sets of conflicting words between time segments.

Let \( w_{ij} \) denote the \( i \)-th unique word in the \( i \)-th confusion bin with confidence \( c_{ij} \in [0,1] \) and frequency \( f_{ij} \in [0,1] \). ROVER picks a word \( w_i^* \) for this bin using the following decision rule:

\[
\text{Weighted ROVER: } w_i^* = \arg\max_{w_i} \left[ \alpha f_{ij} + (1 - \alpha) c_{ij} \right] \tag{2}
\]

where \( \alpha \in [0,1] \) is the weight given to the word frequency \( f_{ij} \). ASR system confidence estimation is a challenging problem and has been the subject of several works [38–41]. Confidence estimation systems often are not perfect, and hence not desirable for the analysis of the diversity-fusion performance link that we are exploring in this paper. Hence, we initially use an oracle confidence estimator for our experiments to get a lower bound on the analysis (we consider automatically estimated confidence scores in Section 3.2). We align the hypothesis word sequence with the reference transcript and set the confidence score of the \( j \)-th hypothesis word \( w_j \) as

\[
\text{Oracle Confidence: } c_j = I(w_j \text{ is correct}) \tag{3}
\]

where \( I \) is the indicator function. This oracle confidence finds the lower bound on the WER after fusion using N-best ROVER.

1http://www.npr.org/2012/10/03/162258551/transcript-first-obama-
romney-presidential-debate
3sail.usc.edu/data.php

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Table 2: This table summarizes the testing set 1-best WERs for various ASR systems. The systems trained on the HUB4 data set provide the lowest WERs while those trained on the ICSI data set give the highest WER. M3 models perform the best out of the three models trained for each data set except WSJ for speaker JL.

<table>
<thead>
<tr>
<th></th>
<th>HUB4</th>
<th>WSJ</th>
<th>ICSI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MR</td>
<td>BO</td>
<td>JL</td>
</tr>
<tr>
<td>M1</td>
<td>31.7</td>
<td>33.9</td>
<td>45.7</td>
</tr>
<tr>
<td>M2</td>
<td>29.0</td>
<td>30.4</td>
<td>43.9</td>
</tr>
<tr>
<td>M3</td>
<td>28.2</td>
<td>29.7</td>
<td>43.4</td>
</tr>
</tbody>
</table>

Table 3: This table summarizes the testing set 1-best WERs for various ASR systems after 10-best ROVER under various conditions. ‘+’ denotes fusion of N-best list across training data sets and/or systems. E.g. the M1 + M2 + M3 row for the WSJ data set indicates that we fused the top hypotheses from the M1, M2, and M3 models before performing ROVER. Confidence-weighted ROVER performs better than both unweighted ROVER and the lowest WER (oracle) hypothesis in the N-best list. We have not included the WERs for the latter in this table due to lack of space.

<table>
<thead>
<tr>
<th></th>
<th>HUB4</th>
<th>WSJ</th>
<th>ICSI</th>
<th>WSJ + HUB4 + ICSI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MR</td>
<td>BO</td>
<td>JL</td>
<td>MR</td>
</tr>
<tr>
<td>M1</td>
<td>28.7</td>
<td>31.6</td>
<td>43.2</td>
<td>36.2</td>
</tr>
<tr>
<td>M2</td>
<td>25.9</td>
<td>28.2</td>
<td>41.4</td>
<td>34.4</td>
</tr>
<tr>
<td>M3</td>
<td>24.9</td>
<td>27.1</td>
<td>40.8</td>
<td>33.2</td>
</tr>
</tbody>
</table>

Setting $\alpha = 1$ gives the unweighted ROVER which does not use any word confidence scores.

Unweighted ROVER: $w^*_i = \arg\max_{w_{ij}} f_{ij}$. (4)

Most works on ASR system ensembles use this unweighted variant. We next present our experiments and analysis.

3. Experiments and Analysis

Table 3 shows the testing set WERs for various system combinations using 10-best ROVER. We created the merged 10-best list by picking equal number of top hypothesis from the individual 10-best lists. For example, the fused N-best list for the M1 + M2 + M3 results using the WSJ data set was created by taking the top 3 hypotheses from each individual list. We also show results when the top hypothesis from each of M1, M2, and M3 models from the three training sets WSJ, HUB4, and ICSI were merged to create a single 10-best list.

We present two sets of results using unweighted ROVER and confidence-weighted ROVER. We make the following observations from Table 3:

1. Both unweighted and confidence-weighted 10-best ROVER result in lower WER than the 1-best WERs in Table 2. The former gives only a marginal improvement over the 1-best WER while the latter gives a significant improvement.

2. Confidence-weighted 10-best ROVER gives significantly lower WER than 10-best unweighted ROVER.

3. Fusion of top 3 hypotheses from the M1, M2, and M3 (in the M1 + M2 + M3 rows of Table 3) systems results in a significant WER reduction over individual systems for confidence-weighted ROVER. However, it does not always reduce the WER for unweighted ROVER.

4. Fusion of top 3 hypotheses from the WSJ, HUB4, and ICSI data sets for each system (in the WSJ + HUB4 + ICSI columns of Table 3) results in a significant WER reduction over individual systems for confidence-weighted ROVER. It is also better than individual data set-dependent systems when using confidence-weighted ROVER. But this is not necessarily the case for unweighted ROVER.

5. Fusion of the top hypothesis from WSJ, HUB4, and ICSI across the three systems (M1, M2, and M3) gives the lowest WER (bottom-right corner of Table 3) when using confidence-weighted ROVER.

The above observations from Table 3 indicate a link between the diversity of the N-best list being fused and the choice of fusion scheme. We discuss it in the next subsection.

3.1. Diversity-Fusion Performance Link

We first define the diversity of an N-best list of word hypotheses before exploring its link with the decision rule. Let $\mathcal{H} = \{h_1, \ldots, h_N\}$ be a set of hypothesis sentences in an N-best list. The average pairwise WER of the list defined as

$$D(\mathcal{H}) = \frac{2}{N(N-1)} \sum_{n=1}^{N} \sum_{m>n} \mathcal{E}(h_n, h_m)$$ (5)

is an intuitive measure of the diversity of the N-best list where $\mathcal{E}$ computes the WER between two hypotheses. $D$ is closely re-
We presented an empirical link between diversity of an N-best list and the WER after ROVER fusion. ROVER WER is highly correlated with a linear function of average N-best WER and N-best diversity. This relation explains many of our empirical observations, such as consistently better performance of confidence-weighted ROVER and reduction in ROVER WER with increasing N-best diversity. Our work shows that there is great incentive for designing diverse ASR systems and accurate confidence estimators. Future work should perform theoretical analysis of the presented link and informed diversity-promoting design of ASR systems.
5. References


