ABSTRACT

Spoken language identification (LID) technologies have improved in recent years from discriminating largely distinct languages to discriminating highly similar languages or even dialects of the same language. One aspect that has been mostly neglected, however, is discrimination of languages for multilingual speakers, despite being a primary target audience of many systems that utilize LID technologies. As we show in this work, LID systems can have a high average accuracy for most combinations of languages while greatly underperforming for others when accented speech is present. We address this by using coarser-grained targets for the acoustic LID model and integrating its outputs with interaction context signals in a context-aware model to tailor the system to each user. This combined system achieves an average 97% accuracy across all language combinations while improving worst-case accuracy by over 60% relative to our baseline.

Index Terms—Language identification, multilingual

1. INTRODUCTION

Automatic speech recognition (ASR) systems are becoming increasingly ubiquitous in today’s world as more and more mobile devices, home appliances and automobiles add ASR capabilities. Although many improvements have been made in multi-dialect [1, 2], multi-accent [3, 4] and even truly multilingual [5, 6, 7] ASR in recent years, they often only support a small subset of languages [8]. In order to get a satisfactory Word Error Rate (WER) for a larger range of languages, language identification (LID) models have been combined with monolingual ASR systems to allow utterance-level switching for a larger set of languages [9] with reasonable accuracy, even over a set of up to 8 candidate languages.

Supporting many dozens of distinct languages, however, can lead to both low LID accuracy and high computational load from running many recognizers in parallel. This is even further complicated by the existence of recognizers for multiple locales (language-location pairs) for the same language, such as American English and British English. Fortunately, only a small percentage of people can speak more than three languages fluently [10], thus greatly constraining the range of possible classifications for a given user. In the case of bilingual speakers, LID is as simple as a binary classification.

Such prior knowledge has been incorporated into LID systems to improve accuracy. In [11], the tuplemax loss function was introduced to incorporate prior knowledge of installed dictation locales directly into the training of the LID model and achieved nearly a 40% relative improvement in LID accuracy over their baseline (cross-entropy loss) system, even with 79 candidate locales. However, there are three practical limitations to their analysis as it relates to common LID use cases. The first is that the majority of both the training and evaluation data in [11] was collected from monolingual speakers, creating a mismatch with the conditions under which the LID system would be used. This is in fact quite common in the LID literature, as even standard benchmarks such as the NIST Language Recognition Evaluation (LRE) [12] do not currently make such a distinction in the datasets they use. The second limitation is that the system was allowed to run on long utterances with overlapping windows and no latency constraints, an impractical assumption for a deployed dictation system. Finally, accuracy is reported as an average of pairwise language identification tasks without taking into account the relative frequency of the language pairs within the user population.

In this paper, we demonstrate how our method of incorporating prior knowledge about usage patterns into our LID system for dictation allows us to make highly accurate decisions for multilingual speakers across a space of over 60 locales [13] while keeping latency low. We then present in-depth error analysis methods for on-device language ID systems, including a novel metric, Average User Accuracy (AUA), that leverages statistical information about the frequency of installed dictation locales to better capture the expected experience across a population of users than previous metrics.

2. SYSTEM OVERVIEW

Our LID system is composed of two stages: an acoustic model and a context-aware model. The former is responsible for making predictions based on the evidence encompassed

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in the speech signal, whereas the latter is responsible for making final predictions by integrating the posteriors produced by the acoustic model with assorted interaction context signals. These context signals encompass information about the conditions under which the dictation request was made, including information about installed dictation locales, the currently selected dictation locale and whether the user toggled the dictation locale before making the request. The context information is also essential in the situation when the speech signal is too short for the acoustic model to produce a reliable prediction (e.g., short ambiguous utterances such as /nan/, which could be the negative “nein” in German or the number “nine” in English if the user has both English and German installed). The predictions provided by this two-stage LID system are then used to select the correct monolingual automatic speech recognition (ASR) model for the given request, similar to the system described in [9].

2.1. Acoustic model

Our acoustic model uses standard 40-dimensional Mel-filter bank features as input. The features are extracted with the standard window length of 25ms and window shift of 10ms with mean normalization applied afterwards. Before any feature vectors are processed by the acoustic model, the audio signal is pre-processed by a speech activity detector to avoid processing audio that is mainly non-speech. The acoustic LID model starts processing audio once a minimum speech duration threshold is met.

The targets of the acoustic model were initially the locales themselves. However, it can be quite difficult to train the model to discriminate between locales due to two primary reasons. The first is that the ground truth labels for locale can be noisy due to users picking locales based primarily on location, rather than accent or dialect (e.g., expatriates using the locale of their current country, rather than their native country). The second is that some locales can be quite similar acoustically (e.g., American English and Canadian English) and differ primarily in other non-acoustic areas, such as the language model. Thus, we experiment with other choices of targets for the acoustic model by clustering locales together into target classes (see Section 4.1) based on language and similarities with other locales for the same language.

Regardless of the choice of target class during training, we want the acoustic model to predict language posteriors during inference. This allows the context-aware model described in Section 2.2 to better handle situations like those described above where a user may speak a given language $l$ in a style consistent with one locale $l_{\alpha}$ of language $l$, but only have a different locale $l_{\beta}$ of language $l$ installed. Therefore, while we may train with separate classes for locales of the same language (see Sections 4.1 and 4.2), we simplify the determination of language during inference by taking the maximum of all logits from $y$ that map to each language.

We also investigated various neural network architectures in our preliminary experiments, including variants of LSTMs [14], CNN-BLSTMs [15], models with self-attention [16], etc. Even after hyperparameter tuning, we did not observe any particular architecture to be substantially better than another. A key component of all the well-performing models, including the LSTM-based ones, turned out to be temporal pooling layers [17], a key feature of state-of-the-art X-vector LID systems [18]. Our final model, summarized in Table 1, consists of a CNN frontend and applies mean and standard deviation temporal pooling. The total number of trainable parameters is 8M.

![Table 1: Acoustic model architecture.](image)

2.2. Context-aware model

The context-aware model serves two main goals. The first is to leverage aforementioned context under which the dictation request was made to improve the recognition accuracy. The second goal is to resolve locale posteriors from the language posteriors produced by the acoustic model during inference. To accomplish these goals, we chose a simple architecture: first, we project language posteriors to locale posteriors by setting each locale $l$ posterior to the its corresponding language $l$ posterior. Next, we mask out posteriors for all locales that are not installed on the device and re-scale the remaining posteriors to sum to 1. Finally, we integrate these masked posteriors with the context signals in a naïve Bayes model trained using statistics gathered from internal users during the development process. The naïve Bayes model was chosen because it allowed us to reason about the conditional probabilities being used in the model without requiring a large amount of data. This interpretability allowed us to easily debug issues and tune thresholds for the model during the development process as more data became available. Additionally, although the independence assumption does not hold for some features (for example, currently selected dictation locale is indeed dependent upon the list of installed dictation locales), naïve Bayes classifiers work surprisingly well under such conditions [19].
3. SYSTEM EVALUATION

3.1. Average User Accuracy

As mentioned in Section 3.1, most speakers can only dictate in up to three languages. The overall accuracy across all supported locales is thus not representative of the target application. Accuracy assessed for smaller tuples of locales (e.g., pairs and triples) reflects the nature of the target application much more closely. However, for the sake of model comparison, a scalar representation of a model’s overall performance is more useful. One such scalar representation is the average of these tuple-wise accuracies. This is still not representative of the real world usage patterns, though, because the frequency of observing specific locale tuples depends on the size of the population speaking the given languages.

To address this, we developed a custom metric which we refer to as Average User Accuracy (AUA). AUA allows us to better reflect population-level usage patterns in model evaluation and thus get a better intuition behind what the average user’s experience is like while using the LID system. We compute AUA as a weighted average of the accuracies for the top-N most frequently used locale tuples, where the weights are proportional to the average number of monthly users for the given tuple. To compute locale tuple accuracy for a tuple $T$ containing $m$ locales $\ell_1, \ell_2 \ldots \ell_m$, we first run the LID system on only utterances that have all locales in $T$ installed (thus restricting samples to multilingual speakers, a key differentiation from previous work) and compare the predicted locale for each utterance to the correct ground truth locale. Because there can be some imbalance in number of utterances available for each ground truth locale within $T$, we compute the locale tuple accuracy for $T$ as an unweighted average of the accuracies for subsets of utterances corresponding to each ground truth locale, rather than the overall accuracy over all utterances combined.

3.2. Worst-case performance

Besides the AUA which serves as our primary metric, special attention is paid to the worst-case performance of the model. We focus on the aforementioned accuracies specific to the ground truth locales within each locale tuple because there could be significant differences in these accuracies due to the model being biased towards one locale or another within a given tuple. An extreme case of this was illustrated by analysis of the en-IN (Indian English) and hi-Latn (Hindi transliterated to Latin characters) locale tuple, where the model was heavily biased towards Hindi despite having a reasonable average score. Analyzing this pair helped to expose difficulties with accented speech in the en-IN locale (as well as other locales) that were previously undiscovered and led us to the decision to model some locales for the same language as separate targets during training (see Section 2.1).

4. RESULTS

We report results for an internal corpus composed of 128k dictation utterances from strictly multilingual speakers with corresponding interaction context information. The AUA weights are based on average number of unique monthly users for each locale tuple and is restricted to the top-100 most commonly used locale tuples. A fixed window size of 2 seconds of audio (starting after speech activity is detected) is used during decoding in all reported experiments with the exception of Section 4.4 which deals with flexible window sizes. Additionally, to get a fairer comparison of acoustic models in Sections 4.1 and 4.2 we set all context signals except for the list of installed dictation locales to zeros (i.e., to ignore the signal) in order to minimize the effect of the context-aware model and instead simply mask out the posteriors for the uninstall dictation locales.

4.1. Acoustic Model Training Strategies

We initially compared two strategies of training the model to predict language posteriors using locale-annotated training data. In the first case ($M_{\text{langs}}$), we train the model with locales as targets and then max-pool locale posteriors to language posteriors as described in Section 2.1. In the second case ($M_{\text{langs+}}$), we combine data from all locales associated with a particular language together before training and then train the model with languages as targets. Because the distribution of the training data is not completely even, neither across languages nor across locales, we employ class-specific cross-entropy weights during training. We conclude based on the results presented in Table 2 that $M_{\text{langs}}$ yields better results in terms of AUA.

4.2. Improving worst-case performance

Analysis of worst-case performance revealed that en-IN was successfully classified by $M_{\text{langs}}$ in only 38% of trials for the (en-IN, hi-Latn) locale tuple. The performance of hi-Latn in the same locale tuple was 81%, leading to an unweighted average of 59.5%. Despite this locale tuple accuracy being low, the weight of this locale tuple is not high enough to sway the overall AUA, highlighting the importance of conducting worst-case performance analysis.

We observed that the en-IN was underrepresented in the pooled English training data. With the intent of keeping the number of training samples for all classes balanced, we decided to model en-IN as a separate language class $M_{\text{en-IN}}$. Training $M_{\text{en-IN}}$ in this way improved en-IN recognition accuracy to 66% without any meaningful change in AUA. Further, we hypothesized that because of large variability of the dialects and accents present in the English class, the model could benefit even more by separating English into more fine-grained language classes than just en-IN. Hence, in our final model $M_{\text{en-IN+L2}}$, we defined three separate classes denoted...
as en-L1, en-L2 and en-IN, where en-L1 is composed of locales where English is natively spoken and en-L2 is composed of locales where English is spoken as a second language (excluding en-IN). This composition of the training data led to significant improvements in worst-case performance for multiple locales as shown in Fig. 1 without significantly affecting AUA.

| Model      | $M_{\text{locales}}$ | $M_{\text{langs}}$ | $M_{\text{en-IN}}$ | $M_{\text{en-IN} + L2}$ |
|------------|-----------------------|--------------------|---------------------|------------------------|
| AUA        | 92.2%                 | 92.9%              | 92.8%               | 92.5%                  |
| Worst-case | 45.9%                 | 38.3%              | 58.5%               | 66.1%                  |

Table 2: Comparison of acoustic model training strategies

4.3. Effect of Context-Aware Modeling

Incorporating the context-aware model does more than simply mask out posteriors for locales not installed on the user’s device. The model also takes into account the currently selected dictation locale and whether the user toggled to this locale directly before making the request. These features are helpful in situations where the acoustic model is not particularly confident in any of the locales, as well as when the user has multiple locales installed that map to the same language (for example, hi-IN and hi-Latn are both Hindi, but use the Devanagari and transliterated Latin scripts, respectively). By utilizing the context-aware model to incorporate the context signals, we improve AUA from 92.5% to 97.0% while also improving the worst-case locale tuple accuracy from 66.1% to 75.1% (see Figure 2).

4.4. Incremental Inference

One benefit of the temporal pooling layer mentioned in Section 2.1 is that allows for variable-sized input during decoding. We conducted experiments to see how well the combined LID system generalizes on short inputs under 2 seconds in length and found that we can get highly accurate results in some cases even with only 1 second of speech. We used this fact to reduce average latency using the following strategy:

- Run LID system on $t_{\text{min}}$ seconds of audio.
- If maximum posterior below confidence threshold $c$, run again on ($t_{\text{min}} + t_{\text{interval}}$) seconds of audio.
- Continue until maximum posterior exceeds $c$ or we hit $t_{\text{max}}$ seconds of audio.

After tuning these parameters to balance accuracy and latency with the computational load of running the model on-device, we found that we could reduce average latency from 2 seconds to 1.2 seconds without reducing AUA by more than 0.05% absolute. The intuition behind the lack of AUA degradation is that most utterances that exceed $c$ for a given locale $\ell$ after only a short amount of audio (e.g., $t_{\text{min}}$ seconds) are still classified as $\ell$ when more audio context is given. This is consistent with the robustness of temporal pooling layers to short audio segments demonstrated in [17]. By reducing latency in this manner, we not only improve the user experience, but also reduce the computational load of running multiple recognizers by stopping the recognizers for all other languages besides the detected one early in the request.

5. CONCLUSION

In this work, we present a set of modeling and analysis techniques for improving the performance of spoken language identification systems for multilingual speakers. We do this by incorporating prior knowledge about the usage patterns of such speakers into both the training and evaluation of language ID systems to improve both average and worst-case performance. By using these techniques, we achieve our final model that achieves 97% AUA with less than 2 seconds of audio on average, all while keeping worst-case accuracy for multilingual speakers above 75%.
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