ACOUSTICS BASED INTENT RECOGNITION USING DISCOVERED PHONETIC UNITS FOR LOW RESOURCE LANGUAGES

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ABSTRACT

With recent advancements in language technologies, humans are now interacting with technology through speech. To increase the reach of these technologies, we need to build such systems in local languages. A major bottleneck here are the underlying data-intensive parts that make up such systems, including automatic speech recognition (ASR) systems that require large amounts of labelled data. With the aim of aiding development of dialog systems in low resourced languages, we propose a novel acoustics based intent recognition system that uses discovered phonetic units for intent classification. The system is made up of two blocks - the first block generates a transcript of discovered phonetic units for the input audio, and the second block which performs intent classification from the generated phonemic transcripts. Our work presents results for such a system for two languages families - Indic languages and Romance languages, for two different intent recognition tasks. We also perform multilingual training of our intent classifier and show improved cross-lingual transfer and performance on an unknown language with zero resources in the same language family.

Index Terms— Intent, Low Resource, Cross Lingual, Multilingual, Long short term Memory

1. INTRODUCTION

In order to bring technology closer to humans, it is important to provide accessible mechanisms of interaction. Speech is regarded as the most natural form of interaction for humans and improvements in language technologies such as Automatic Speech Recognition and Speech Synthesis have made speech technology much more accessible.

However, lack of annotated data is a major bottleneck for scaling speech technologies to new languages and domains. Therefore, it is useful to design techniques that can perform well in low data scenarios to accelerate the process of building a language technology stack for low resource languages. A fundamental resource required to build such a stack is a phonetic lexicon - something that translates acoustic input to textual representation. In this paper, we present a novel approach to perform intent recognition purely from acoustics using such a lexicon. A block diagram representing such a system is shown in Figure 1. Through our approach, we bypass the need to build data intensive systems parts like an ASR system for every language and demonstrate deployable performance for intent recognition using discovered phonetic units.

We test the performance of our system on two language families - Indic and Romance languages, each having a different intent recognition task. We also perform multilingual training for our intent classifier and evaluate the systems in the context of blind languages - languages not present in the training dataset within the same language family. This simulates a zero resource scenario and helps us understand the extent of cross-lingual transfer between languages for our acoustics based intent recognition system. We find that a multilingually trained classification model performs significantly better than a monolingually trained model for an unknown language.

2. RELATED WORKS

To the best of our knowledge, this paper is the first attempt in literature to use the phonetic units for intent classification. An important component of the system is the first block that generates phonetic units, thus creating phonemic transcription of the audio. There have been numerous attempts\[1, 2\] to discover such acoustic units in an unsupervised fashion. In \[3\], authors presented an approach to modify the speaker diarization system to detect speaker-dependent acoustic units. \[4\] proposed a GMM-based approach to discover speaker-independent subword units. However, their system requires a separate Spoken Term Detector. Our work is closest to \[5\] where authors discover symbolic units in an unsupervised fashion for speech to speech translation. Contrary to this work, we employ the symbolic units generated by Allosaurus \[6\] which is trained in a supervised fashion.

3. DATASETS

We study the performance of our acoustic based intent recognition system for two language families - Indic Languages and Romance Languages. For each family we use a different dataset and each language family has a different intent recognition task.
### 3.1. Dataset for Indic Languages

We use Google’s Taskmaster-1 Dataset [7] for Indic Languages which contains data for user interactions with an autonomous dialogue system collected using the Wizard of Oz methodology [8]. The user dialogues are present as written transcripts of the conversations in English. The dataset contains labelled intents and slots for the conversation. We extract the sentence responsible for the labelled intent from the dataset and create an intent recognition dataset. We obtain 3243 utterances in total distributed amongst 6 intents as shown in Table 1. After creating the intent classification dataset, we translate the transcripts in English into four Indic languages - Hindi, Gujarati, Bengali and Marathi, using the Google Translate API. The translated text was used to synthesize audio using the Google Text-To-Speech API for Hindi, Gujarati and Bengali. CLUSTERGEN [9] was used synthesizing for Marathi voice. The voice quality of Marathi is much worse when compared to the other voices generated from Google’s API. The dataset in each language contains two voices - one male and one female. The audios are then passes into Allosaurus [6] to discover phonetic units and create a phonemic transcription of the audio.

### 3.2. Dataset for Romance Languages

To work with Romance languages, we create an intent recognition dataset from the MultiWoz dataset [10]. The dataset contains a large number of dialogues between humans and robots where each utterance is associated with a json object containing the conversational context. The context has rich information about the intent of humans. The largest context class in the dataset is about the reservation day whose distributions are shown in the Table 2. This class is used as our Romance languages dataset. This dataset is then prepared in a similar way as done for the Indic language, where we translate the original English utterances into 4 different Romance languages - Italian, Portuguese, Romanian and Spanish. The translated text is synthesized with the Google TTS engine, and then transcribed into phonemes with Allosaurus [6].

| Intents                  | Number of Utterances |
|-------------------------|----------------------|
| ordering pizza          | 711                  |
| auto-repair appointment | 484                  |
| order ride service      | 450                  |
| order movie tickets     | 549                  |
| order coffee            | 292                  |
| restaurant reservations | 757                  |

Table 1. Class distribution for the Indic dataset.

| Intents         | Number of Utterances |
|-----------------|----------------------|
| Monday          | 743                  |
| Tuesday         | 718                  |
| Wednesday       | 757                  |
| Thursday        | 738                  |
| Friday          | 763                  |
| Saturday        | 779                  |
| Sunday          | 806                  |

Table 2. Class distribution for the Romance dataset.

### 4. MODELS

A block diagram depicting our acoustics based intent recognition system utilizing a phonemic transcription is shown in Figure 1. The input audio is directly fed into a system that can generate hypothesized phonetic units. For our work, we use the Allosaurus library [6] which can generate language dependent or independent phones. For this work, we employ the language dependent phones. The phonemic transcription is then sent to an intent classifier that does the classification purely based on the generated sequence of phonemes. Such very simple systems can be used to build powerful tools, especially for low resource languages, as shown in [11].

![Fig. 1. Block Diagram showing a general acoustics based intent recognition system.](image)

We use the Naive Bayes classifier as our baseline with add-1 smoothing and absolute discounting. Cross-lingual classification performance was better with absolute discounting for different values of delta. We also investigate a neural network architecture shown in Figure 2 to compare with the baseline results. The architecture is based on LSTMs (long-short term memory) [12] for modeling sequential information where the contextual information is encoded using CNNs (convolutional neural network). The input to the network is a sequence of phonemes \[ x = x_1, x_2, \ldots, x_t, \] where each phoneme is converted into a one-hot vector of size equal to the vocabulary size of the phonemic lexicon. The sequence of input vectors are then passed through an embedding layer. We use a 128 dimensional embedding vector. The embedding layer converts the input sequence into a dense vector representation which is then sent to two 1-d CNN layers with 128 channels with padding such that the size of an embedding is preserved. There are 128 CNN filters and each filter captures different k-gram features, where k is the kernel size. The outputs of each of the CNN’s layers are concatenated to create a long embedding vector corresponding to each phoneme in the sequence. This embedding vector now incorporates con-
This new embedding vector is then passed through the LSTM layer consisting of 128 neurons. The hidden state of the LSTM layer at the final time step is sent to a linear layer for classification. We use a 128 dimensional embedding vector. The embedding vector is sent to the 1-d CNN layers of channel size 128 with padding such that the original embedding size is maintained for each CNN filter. There are 128 CNN filters and each filter captures different k-gram features, where k is the kernel size.

**5. EXPERIMENTS**

We test our acoustics based intent recognition system for two sets of languages across two different language families - Indic and Romance language families. We perform monolingual and multilingual training for both baseline and our proposed neural network architectures and test the model performance for multiple languages.

**5.1. Monolingual Training Results**

In this section we present results for intent classification architectures trained on a single language. Table 3 presents the classification results for Indic languages and Table 5 for Romance languages. The diagonal elements in the tables show the classification accuracy for training and testing performed on the same language. The numbers in the bracket show performance with the baseline (Naive Bayes) classifier. We see that our proposed neural network architecture improves on the baseline significantly.

Cross-lingual testing results for monolingually trained classification models are also shown in Tables 3 and 5. The performance is relatively poor when the classification model is trained on only one language due to minimal cross-lingual transfer. Language pairs for linguistically similar languages show higher performance. This can be seen for language pairs Hindi-Gujarati and Gujarati-Marathi in Indic language family and pairs Italian-Portuguese and Italian-Spanish in the Romance language family. These language pairs are also geographically close. The cross lingual results are in general better for the Indic Dataset when compared to the Romance dataset because all Indic languages have some amount of code mixing within them. Therefore, there is a larger cross-lingual transfer of features between any pair of languages in the Indic language family when compared to the Romance language.

**5.2. Multilingual Training Results**

With the aim of improving performance on a language not present in our training set, simulating a zero resource scenario, we train a multilingual model. The training set size is kept the same and the exact same train-test split is used for accuracy scores as used for monolingual results. Let $T = \{L_1, L_2, \ldots, L_n\}$ be the set of languages we use to train the classifier. Then the training set is divided randomly and equally amongst the ’n’ languages present in the training set.

The results for multilingual training can be seen in Table 4 and Table 6 when trained on $n = 3$ languages. The results in bold are for the language not in the training set. The numbers in the bracket show performance with the baseline (Naive Bayes) classifier. We see that our proposed neural network architecture improves on the baseline results significantly in almost all cases.

For a language $L_p$ present in training set $T$, we find that the results are always better than results for a monolingual classifier trained on any one language in $T$ except $L_p$. In other words, the model performs better for all train-test language pairs.

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**Table 3.** Classification Accuracy for monolingual training for Indic Languages - Hindi (Hin), Gujarati (Guj), Marathi (Mar) and Bengali (Ben). The numbers in the bracket are the baseline results using a Naive Bayes classifier.

| Test Language | Hin (Train) | Guj (Train) | Mar (Train) | Ben (Train) |
|---------------|------------|------------|------------|-------------|
| Hin           | 92.0%      | 54.7%      | 43.7%      | 54.3%       |
| Guj           | 52.3%      | 93.3%      | 52.0%      | 63.0%       |
| Mar           | 52.0%      | 66.3%      | 87.7%      | 58.0%       |
| Ben           | 48.0%      | 54.7%      | 45.7%      | 95.0%       |

**Table 4.** Average Classification Accuracy for a multilingually trained model. The languages in bold are the languages that are not present in the train set. The numbers in the bracket are the baseline results using a Naive Bayes classifier.

| Test Language | Hin (Train) | Guj (Train) | Mar (Train) | Ben (Train) |
|---------------|------------|------------|------------|-------------|
| HGM           | 85.3%      | 90.3%      | 75.6%      | 80.7%       |
| HGB           | 87.3%      | 90.0%      | 61.7%      | 90.3%       |
| HMB           | 84.3%      | 62.0%      | 80.7%      | 88.3%       |
| GMB           | 65.3%      | 86.7%      | 83.0%      | 92.0%       |
Table 5. Classification Accuracy for monolingual training for Romance Languages - Italian (Ita), Portuguese (Por), Romanian (Ron) and Spanish (Spa). The numbers in the bracket are the baseline results using a Naive Bayes classifier.

|       | Ita  | Por  | Ron  | Spa  |
|-------|------|------|------|------|
| Train |      |      |      |      |
| Ita   | 88.6 | 74.6 | 76.5 | 89.0 |
| Por   | 82.6 | 62.1 | 59.4 | 89.0 |
| Ron   | 61.3 | 67.2 | 60.7 | 67.2 |
| Spa   | 50.3 | 59.9 | 59.9 | 59.9 |

Table 6. Classification Accuracy for a multilingually trained model. The languages in bold are the languages that are not present in the train set. The numbers in the bracket are the baseline results using a Naive Bayes classifier.

|       | Ita  | Por  | Ron  | Spa  |
|-------|------|------|------|------|
| Test  |      |      |      |      |
| IPR   | 87.0 | 88.9 | 85.4 | 60.4 |
| IPS   | 88.6 | 88.9 | 88.6 | 88.6 |
| IRS   | 88.1 | 41.3 | 86.6 | 86.6 |
| PRS   | 50.3 | 87.8 | 84.9 | 88.3 |

The performance for an unknown language $L_u \notin T$ can further be improved by injecting a very small amount of data for $L_u$ in the training set. We added training data for language $L_u$ in increments of a ratio of 0.05 of the training set as shown in Figure 3. We see that introducing even the slightest amount of training data for the unknown language increases its performance significantly while not affecting the performance of the other languages. Figure 3 shows an increase in performance of about 9% for Marathi, 14% for Hindi and 17% for Gujarati only by an injection of data 5% the size of training dataset.

6. DISCUSSION

We presented results for our proposed intent recognition system for two different language families operating on two different datasets. It was shown that performance can be improved for an unknown language within a language family by using multilingual training. This helps in maximal cross-lingual transfer of features for languages that are linguistically and geographically closer to each other. We also found that performance for an unknown language can be improved significantly by introducing a minimal amount of training data for an unknown language.

Our present work was based on synthesized data due to the absence of enough natural speech datasets for intent recognition for low resource languages. Future work can include corroboration of our results with natural speech. The synthesized speech also had little speaker variation in terms of speaker style or prosody though we did include variation in speaker gender. Further investigation into low resourced languages with varied dialects and natural speaker variations will help establish our methods.

7. CONCLUSION

In this paper we present a novel acoustics based intent recognition system that classifies intents directly from user audio and does not require an underlying ASR system. Such a system is especially useful for low resource languages for which we cannot build robust speech to text systems. We also propose an LSTM based neural network architecture for intent classification for phonemic transcripts where the context is incorporated using CNN layers. We investigate the extent of cross lingual transfer and performance on an unknown language for our multilingual intent classifier.
8. REFERENCES

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